NAVAL POSTGRADUATE SCHOOL
Monterey, California

THESIS

OPTIMIZING THE ALLOCATION OF SENSOR ASSETS FOR THE UNIT OF ACTION

by

Stephanie J. Tutton

June 2003

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REPORT DOCUMENTATION PAGE			*Form Approved OMB No. 0704-0188*
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington DC 20503.			
1. AGENCY USE ONLY *(Leave blank)*	**2. REPORT DATE** June 2003	**3. REPORT TYPE AND DATES COVERED** Master's Thesis	
4. TITLE AND SUBTITLE: Optimizing the Allocation of Sensor Assets for the Unit of Action			**5. FUNDING NUMBERS**
6. AUTHOR(S) Tutton, Stephanie			
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000			**8. PERFORMING ORGANIZATION REPORT NUMBER**
9. SPONSORING /MONITORING AGENCY NAME(S) AND ADDRESS(ES) U.S. Army TRADOC Analysis Center Monterey, CA			**10. SPONSORING/MONITORING AGENCY REPORT NUMBER**
11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.			
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release; distribution unlimited			**12b. DISTRIBUTION CODE**

13. ABSTRACT (maximum 200 words):

The U.S. Army's Objective Force is being developed as a faster, lighter, more rapidly deployable alternative to the current force structure. The development of a strategy for the allocation of the Unit of Action's organic sensing assets is necessary to achieve the maximum situational awareness and information dominance required for successful combat operations on the future battlefield. This thesis presents a methodology for finding an appropriate mix and allocation strategy for organic Unit of Action sensors in a given scenario. Three aggregate levels are identified: sensors, platforms, and packages and performance measures are developed at each level. Two optimization models were developed, (1) a Sensor Allocation Model that, given a fixed mix or inventory, allocates assets to target areas on the battlefield, and (2) a Sensor Mix Model that suggests an organic mix of sensors for consideration in developing the Objective Force structure. These models have the additional potential for use as an operational decision support tool for unit commanders. The notional data set used for model development included ten platform types, ten target clusters, ten target categories, four enemy orders of battle, and four outcomes, however these inputs are easily modified based on the requirements of the user or analyst.

14. SUBJECT TERMS Optimization, Objective Force, Unit of Action, Unmanned Aerial Vehicles, Sensors, Sensor Allocation, Mixed Integer Program, MIP, Operations Research			**15. NUMBER OF PAGES** 90
			16. PRICE CODE
17. SECURITY CLASSIFICATION OF REPORT Unclassified	**18. SECURITY CLASSIFICATION OF THIS PAGE** Unclassified	**19. SECURITY CLASSIFICATION OF ABSTRACT** Unclassified	**20. LIMITATION OF ABSTRACT** UL

NSN 7540-01-280-5500

Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std. 239-18

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OPTIMIZING THE ALLOCATION OF SENSOR ASSETS FOR THE UNIT OF ACTION

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requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

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ABSTRACT

The U.S. Army's Objective Force is being developed as a faster, lighter, more rapidly deployable alternative to the current force structure. The Objective Force will feature a smaller in-theater footprint and require the ability to cover a larger area of the battlespace with intelligence-gathering assets.

The development of a strategy for the allocation of the Unit of Action's organic sensing assets is necessary to achieve the maximum situational awareness and information dominance required for successful combat operations on the future battlefield. This thesis presents a methodology for finding an appropriate mix and allocation strategy for organic Unit of Action sensors in a given threat scenario. The mix suggested by the model is robust to uncertainties in sensor performance and target quantity and location. The model presented in this thesis shows great promise for use as a screening tool in support of analysis of alternatives studies as well as in support of Army and Joint warfighting experimentation. The model also has potential for use as an operational decision support tool for unit commanders.

The Unit of Action's sensing capability is represented in this thesis by three levels of aggregation (sensor, platform, and package), for which performance metrics are calculated. The sensor level consists of devices with unique sensing capabilities such as infrared, acoustic, and electro-optical sensors, whose performance is measured by a probability of detection at a certain range against a particular target. The platform level consists of unmanned aerial vehicles (UAV), armed robotic vehicles (ARV), etc, each with the capability of having one or more sensors mounted on the platform. Packages consist of identified platforms that, when teamed together and employed as a single entity, have improved detection capability.

The Sensor Mix Model is an optimization model designed to assist Objective Force developers and analysts with the allocation of sensing assets to target locations on the battlefield, and to suggest opportunities to consolidate individual platforms into new package configurations. Additionally, this model can be modified to assist with the development of the Objective Force structure and organic asset inventory levels in

addition to the development of tactics, techniques, and procedures (TTPs) for sensor employment and allocation on the battlefield.

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ACRONYMS

AMSAA	Army Materiel Systems Analysis Activity
AO	Area of Operations
AOI	Area of Interest
ARV	Armed Robotic Vehicle
CDP	Cumulative Detection Probability
C2	Command and Control
C4ISR	Command, Control, Communications, Computers, Intelligence, Surveillance, and Reconnaissance
CROP	Common Relevant Operating Picture
EOB	Enemy Order of Battle
FCS	Future Combat System
FoS	Family of Systems
IPB	Intelligence Preparation of the Battlefield
OF	Objective Force
SAM	Sensor Allocation Model
SMM	Sensor Mix Model
TTP	Tactics, Techniques, and Procedures
UA	Unit of Action
UAV	Unmanned Aerial Vehicle
UE	Unit of Engagement
UGS	Unattended Ground Sensor

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ACKNOWLEDGMENTS

I would like to thank my thesis team of Professor Matthew Carlyle and Major Donovan Phillips for agreeing to accept me as the thesis student to work on this project six months ago and direct me through a process. Numerous additional thanks go out to the many professors in the NPS OR department who helped further direct me in a forward direction.

Major Bruce Gorsky, at Fort Leavenworth, deserves a special thank you for first thinking up this project and then letting me bend his ear with new ideas.

A special thanks to my two NPS study partners, Captain Michael Margolis and Major Joe Baird for listening to endless UAV search theory situations and allowing me to become a part of their families during our time in Monterey.

My deepest gratitude and thanks goes to Major John Bruggeman, whose willingness to spend endless hours in the optimization lab developing a methodology, working through multiple model changes, writing GAMS code, and just listening to crazy ideas and frustrations, while completing his own thesis was invaluable. I could not have done this without his infinite help and I cannot begin to describe how much I have learned above and beyond this research through his example of professionalism, intelligence, time management, and dedication. Major Bruggeman, you are an example worthy of emulation by anyone.

A final thank you to my parents for just listening at the other end of the phone, they now know more about sensors than most and probably more than they ever wanted.

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EXECUTIVE SUMMARY

The Army Transformation Process is a movement toward lighter, more agile forces with the ability to fight efficiently and effectively as a joint team. The Objective Force concept incorporates and exploits information dominance to achieve its goals. This thesis addresses the development of a methodology for allocating and determining the appropriate mix of organic sensor assets to assist in gaining the superior situational awareness required by commanders.

Specifically, this research attempts to develop a set of optimization models that are robust to uncertainties in sensor performance as well as target quantity and location. Given a fixed set (or inventory) of organic sensors, the Sensor Allocation Model attempts to optimize sensor-to-target cluster assignments, capitalizing on sensor capabilities to provide the highest possible level of target detection. The Sensor Mix Model is designed to assist Objective Force developers and analysts in determining an appropriate mix of organic sensors for the Unit of Action.

The Unit of Action sensing capability is represented in this thesis by three aggregate levels: sensor, platform, and package. The sensor level consists of unique sensing capabilities such as infrared, acoustic, and electro-optical sensors that provide a probability of detection at a certain range against a particular target. The platform level consists of unmanned aerial vehicles (UAV), armed robotic vehicles (ARV), etc, each with the capability of having one or more sensors mounted on the platform. Packages consist of identified platforms that, when teamed together and employed as a single entity, have an increased performance level.

These models are demonstrated using an unclassified, surrogate set of sensor performance data. The data set generated for this thesis was based on the type and format of the classified data currently available from AMSAA. The data set included ten platforms, 175 consolidated packages, ten target clusters, four enemy orders of battle and four outcomes.

This research was sponsored by the U.S. Army Training and Doctrine Command Analysis Center – Monterey, to assist with the development of the Objective Force

structure, and with the development of tactics, techniques, and procedures (TTPs) for sensor employment and allocation on the battlefield. The output from these optimization models have the potential for use as input in future simulation studies. The Sensor Allocation Model has the potential for additional use as an operational decision support tool.

I. INTRODUCTION

A. OVERVIEW

The United States Army is in the process of transforming itself into a faster, lighter, more rapidly deployable force capable of facing any threat in any environment. "The Objective Force is our future full spectrum force: organized, manned, equipped and trained to be more strategically responsive, deployable, agile, versatile, lethal, survivable and sustainable across the entire spectrum of military operations from Major Theater Wars through counter terrorism to Homeland Security" (U.S. Army White Paper, 2002). The Army Vision, which will be realized through the development of the Objective Force and the Transformation Process, is focused on joint operations.

The ability to efficiently and effectively fight as a joint team results in full spectrum dominance, which means U.S. forces, operating unilaterally or with allies, have the ability to defeat any adversary and control any situation across the entire range of military operations. Full spectrum dominance allows any component of the joint fight to leverage any and all assets across the entire operational framework (White Paper, 2000).

The Army's full spectrum force will be built around the Future Combat System (FCS) Family of Systems (FoS). The FCS is envisioned to be an ensemble of manned and unmanned combat systems designed to ensure that the Objective Force is strategically responsive and dominant during operations from small-scale contingencies to full-scale conflict. The OF will incorporate and exploit information dominance to develop a Common Relevant Operating Picture (CROP) and achieve the required battlespace situational understanding (FCSD, 1999). One tradeoff in the Transformation Process and movement toward lighter, more agile forces is a substitution of information superiority for armor and firepower, allowing the OF to strike at the time and place of their choosing.

Organic sensing assets at the Unit of Action (UA) level play a critical role in developing the superior situational understanding that UA commanders require to shape the battlefield and maneuver to positions of advantage. "The key to the success of UA operations is the ability to build and maintain a credible knowledge base in order to know

more about what is going on and dominate the battlespace" (UA O&O 2002). Currently there is little information detailing, or published literature outlining, effective employment strategies of UA organic sensing assets in order to achieve the goal of superior situational understanding.

The United States Army is in the process of developing superior sensing technology but, without a methodology or procedure to assist in determining an effective employment strategy of sensor assets, units will not realize their full sensing capability nor achieve the highest level of situational awareness and understanding.

B. THESIS OBJECTIVE

The U.S. Army Training and Doctrine Command (TRADOC) Analysis Center (TRAC) has been tasked with the design and development of a mathematical model (or models) to recommend sensor assignments or allocations to target areas for the Unit of Action and subsequent sensor employment strategies. The objective of this thesis is to provide to TRAC-Monterey and the U.S. Army a methodology that suggests different allocations and employment strategies for unmanned sensor assets organic to the Unit of Action. Modifications to these models allow for analysis and comparative studies of alternative inventories of sensing assets for use in force design studies.

C. THESIS PURPOSE

Objective Force units will be distinguished from today's Legacy Force units by their ability to maintain what the Army terms the "Quality of Firsts." OF units at all levels, engaged in any type of operation, will "See First, Understand First, Act First, and Finish Decisively" (White Paper, 2002). "These "Firsts" indicate a continuous ability to provide Command, Control, Communications, Computers, Intelligence, Surveillance and Reconnaissance (C4ISR) coverage to achieve a Common Relevant Operating Picture that immediately disseminates the commander's intent, and provides for simultaneous joint maneuver and strikes in order to paralyze the enemy and destroy his ability to continue" (Army Vision, 2002).

This thesis focuses on "See First." OF units detect, identify and track enemy units utilizing intelligence made available from higher echelons and assets organic to the unit. These assets include organic sensors, Special Operations Forces, joint air and ground reconnaissance operations, etc. This thesis develops tools to answer the following two questions:

(1) Given an initial inventory of C4ISR assets, how should they be employed?

(2) What C4ISR assets should be organic to the UA?

This thesis looks specifically at organic Unit of Action sensors and platforms such as unmanned aerial vehicles (UAVs), armed robotic vehicles (ARVs), and unattended ground sensors (UGSs). The Sensor Mix Model (SMM) extends the Sensor Allocation Model (SAM) by treating the initial inventory of assets as the key decision variable, and provides a tool to analyze the mix and allocation of organic sensors by maximizing expected target detections within the UA's Area of Operations.

The SMM does not determine actual detected targets on the battlefield. An expected number of target detections is calculated based on the allocation of sensors suggested by the model prior to the actual employment of assets. This model also does not suggest specific search methods or patterns. Rather, it uses results from search theory to estimate the performance of various allocations of sensors.

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II. BACKGROUND

A. OBJECTIVE FORCE STRUCTURE

Understanding the Objective Force structure is important as a means to determine responsibility levels and mission requirements. The OF structure is centered around Units of Employment (UEs) -- Echelons at and above Corps level -- and Units of Action (UA) of various sizes. The UA represents a brigade, battalion or company-size unit.

The UE is a tailorable force that can be rapidly modified based on the threat, region, or level of conflict. Figure 1 below shows the modular nature of subordinate UAs and the commonality in the structure of their organization. This modularity permits rapid initial tailoring as well as re-tailoring during the course of an operation and allows adaptation to a changing situation (UA O&O, 2002). The Unit of Action is the tactical echelon of the OF and the *brigade-sized* Unit of Action is the level considered for the Sensor Mix Model and this thesis.

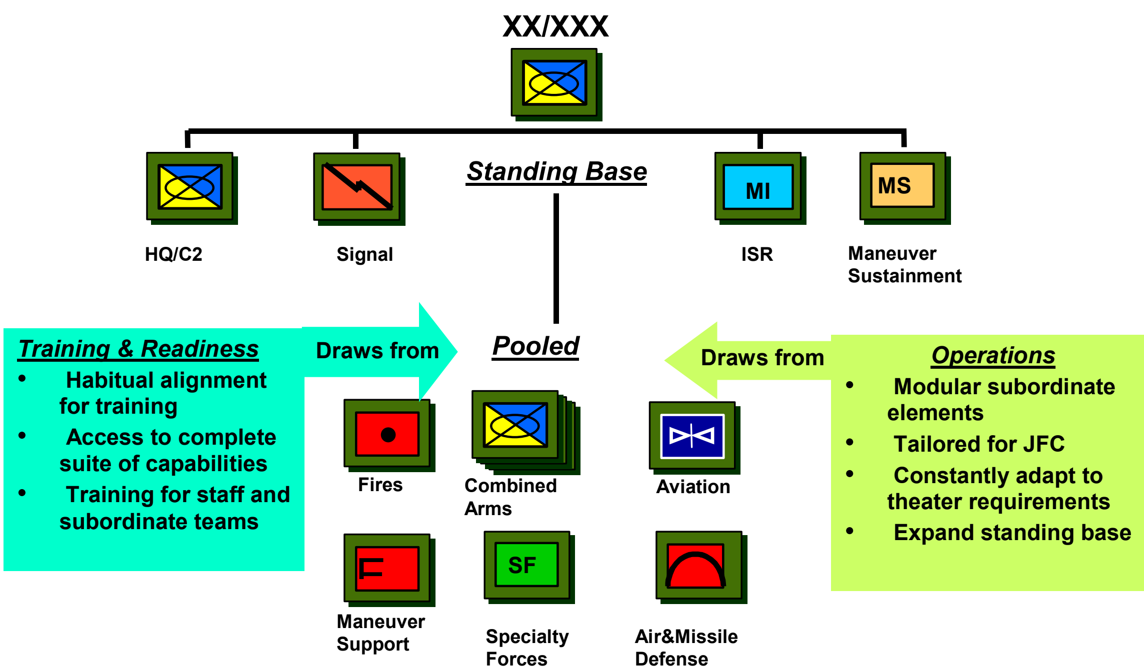

Figure 1. Unit of Employment Organization (From Ref. UE O&O, 25Nov2002)

1. Divisional Unit of Employment

The Divisional Unit of Employment has operational command and control of the UA and has several core functions that include: facilitate deployment, develop the situation before forces are joined, gain information superiority, synchronize operations and combat power, provide enablers to the Unit of Action, and shape and isolate the battlespace (UA O&O, 2002). The Divisional UE continues the intelligence gathering process begun at higher echelons and in coordination with joint assets. This process encompasses layered intelligence collection that includes deployment of Special Operations Forces into the threat region fused with national and joint sensing assets operating over the region (UA O&O, 2002).

The Divisional UE is responsible for creating the Common Relevant Operational Picture (CROP) and providing an accurate assessment of conditions in the theater. The Divisional UE makes the assumption that it can provide the fidelity of information needed for the UA to remain offensive and maneuver to positions of advantage (UA O&O, 2002). The Unit of Action, however, must be prepared to fight immediately upon entering the theater of operations and uses the CROP for initial planning during the Entry Operations and Actions Before Forces are Joined stages. Sections B.1 and B.2 in this chapter further define these stages.

2. Unit of Action

The Unit of Action is responsible for integrating organic and supporting Intelligence, Surveillance, and Reconnaissance (ISR) assets, fires, and Command and Control (C2) immediately upon entrance into the theater of operations. Once the UA is committed, the Divisional UE immediately begins refocusing its intelligence assets and shaping the battlefield for the follow-on fight (UA O&O, 2002).

An extremely vulnerable phase of any military operation is the transitional period when a unit assumes command and control from another unit. The Sensor Mix Model provides a method for the UA commander to utilize the UE's Intelligence Preparation of the Battlefield (IPB) and the CROP while enroute to the theater of operations. The ability to immediately deploy sensing assets and begin shaping operations within the UA Area

of Interest allows continued development of the tactical infosphere and is critical to reducing operational risk to soldiers during the UA's acceptance of Battle Command from the UE.

B. STAGES OF CONTACT

The Objective Force concept describes five main stages of contact with enemy forces: Entry Operations, Actions Before Forces are Joined, Actions during Combat, Tactical Assault and Transitions. Each stage requires a specific level of situational understanding and intelligence integration sufficient for accomplishment of the mission and to achieve success on the battlefield. "Future OF engagements will be characterized by new tactical principles based upon the development of the situation out of contact, a balanced combination of standoff capabilities, skillful maneuver, and tactical assault to achieve simultaneous decisions at multiple locations" (UA O&O, 2002).

The Sensor Mix Model focuses on the development of an effective assignment of sensing platforms to potential target locations during the Entry Operations and Actions Before Forces are Joined stages. However the model can be modified to include time periods and allocate sensors during any stage of contact. The goal is to maximize the expected number of targets detected in designated search areas. The Sensor Mix Model is a tool designed to upgrade the intelligence integration effort from "sufficient for accomplishment of the mission" to "superior situational dominance," based on the optimization of sensor-to-target pairings with available UA organic assets, thereby reducing casualties and decreases in operational momentum.

1. Entry Operations

Entry Operations are characterized by speed, precision, and knowledge. During operational planning, the UA commander must develop a plan to immediately and effectively begin gathering intelligence within the UA's Area of Operations and begin providing updates to the CROP. The UA commander must capitalize on the situational awareness provided by the UE through the CROP, quickly deploy sensing assets, and fuse all intelligence assets into an intelligence picture that provides reasonable certainty

about the environment in which the UA will operate. "The access that the UA has to joint intelligence capabilities enables the UA's ability to prepare the battlespace even while still enroute to the point of entry" (UA O&O, 2002).

2. Actions Before Forces are Joined

Actions Before Forces are Joined closely follows the Entry Operations stage. This stage completes the transition of Battle Command from the UE commander to the UA commander. "The UA continues to leverage the UE IPB, develop the situation out of contact, decide when and where to fight, set the conditions to ensure tactical success and maneuver to positions of advantage" (UA O&O, 2002). The UA commander must quickly deploy unit organic sensing assets in a near optimal configuration to identify targets, target clusters and locations, maneuver routes, and gain the situational awareness and situational understanding needed in order to conduct tactical operations during the follow-on stages of contact.

Figure 2 below depicts the UA's reliance on non-organic and organic ISR capabilities at different stages in an operation.

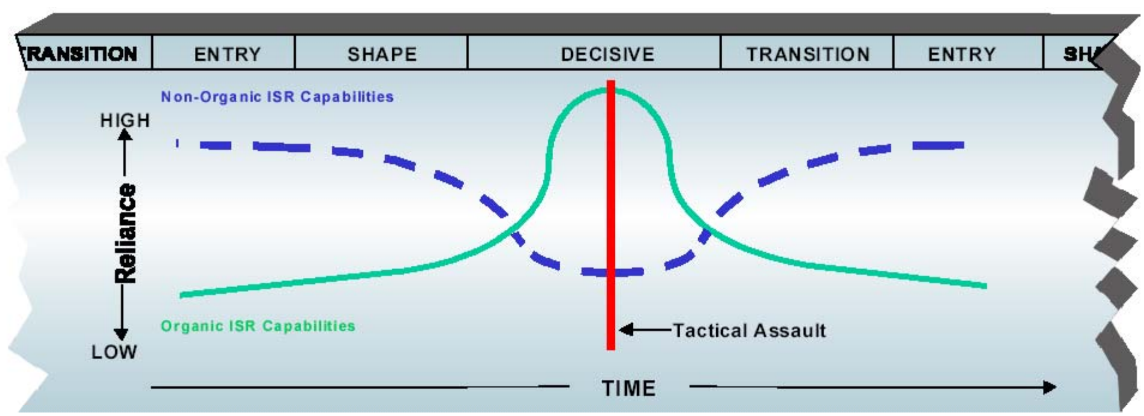

Figure 2. Non-Organic/Organic ISR Relationship (From Ref. UA O&O, 2002)

The focus of the model is at the decisive stage when the UA begins to reduce reliance on non-organic ISR assets and begin deployment of organic ISR assets. The Sensor Allocation Model can assist unit commanders with the allocation of organic assets to target areas on the battlefield in an effective manner.

C. COMMON RELEVANT OPERATING PICTURE

The UA's effectiveness and performance depend on a pervasive, robust C4ISR network to provide a CROP to all Future Combat Systems (FCS) (UA O&O, 2002). The UA commander continues to increase the fidelity of the CROP by deploying organic sensing assets as a means to locate, verify, confirm and eventually target enemy locations. "A tactical infosphere (See Figure 3 below) enables layered and overlapping information activities to push actionable information from external sensors, and the quality and quantity of information increases as additional sensors are applied to the ISR process" (UA O&O, 2002).

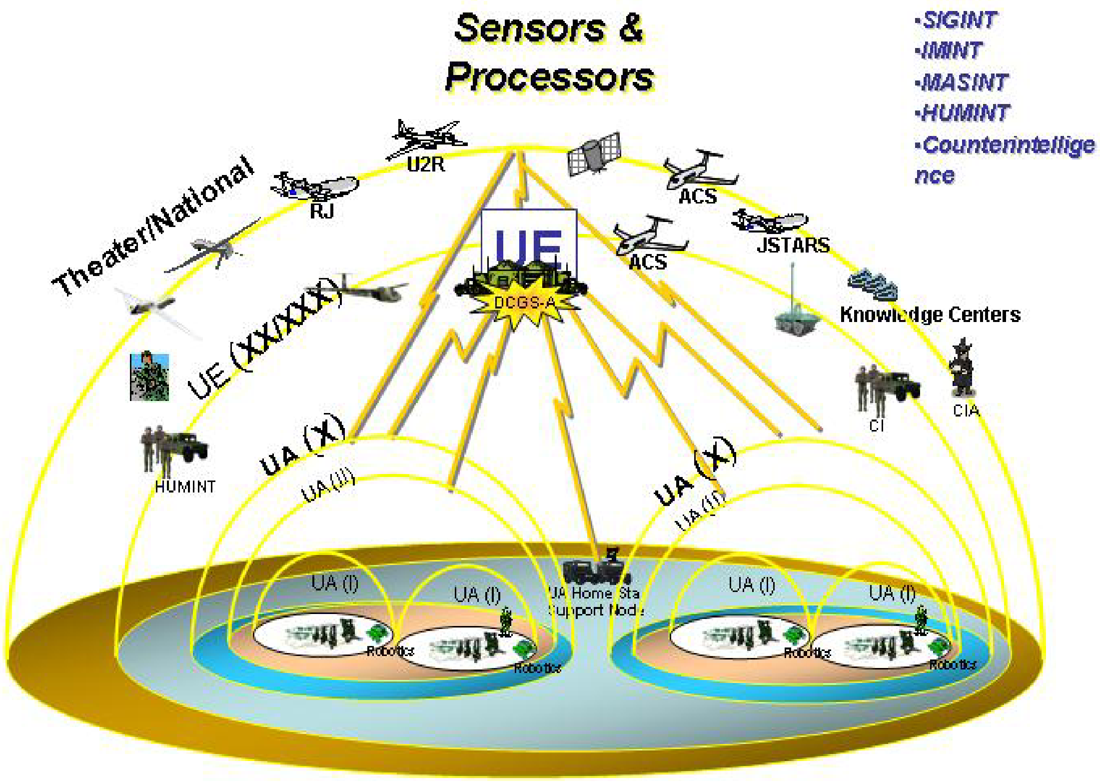

Figure 3. Tactical Infosphere (From Ref. UABML, 2002)

Each level of the Objective Force provides inputs to the tactical infosphere. The infosphere increases as more sensor assets are utilized during the ISR process (UA O&O, 2002). The outer-most hemisphere in Figure 3 represents the battlespace at the highest or

theater/national level. The term Battlespace is a conceptual term and defined as an area or space, where an understanding of environmental factors, terrain, enemy disposition, and ability to apply combat power, allows the commander to accomplish the mission (UA O&O, 2002). As OF units deploy to the Theater of Operations, the Battlespace is further delineated geographically into Areas of Interest, Influence and Operations.

The Area of Interest is the largest physical area in the Battlespace and provides boundaries for the commander to focus intelligence and information gathering operations. Contained within the Area of Interest is an Area of Influence, in which a commander has the ability to directly influence operations in the area. Finally, the Area of Operations is the geographical area in which the UA commander employs organic, assigned and supporting systems for unit mission accomplishment. This area will always lie within the Area of Influence (UA O&O, 2002). Figure 4 indicates the relative sizes (not to scale) of the above geographical areas.

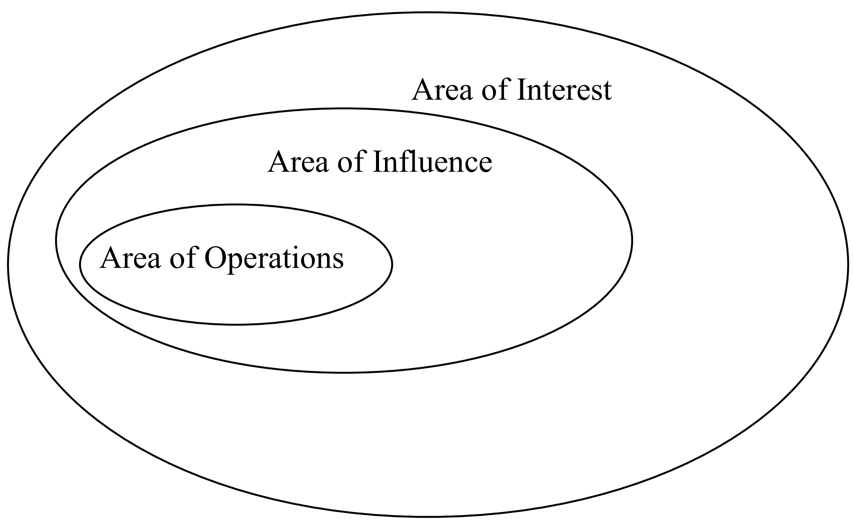

Figure 4. Geographical Areas in the Battlespace

III. METHODOLOGY

A. OVERVIEW

This thesis develops a mathematical programming model to analyze the mix and allocation of organic UA sensor assets using an optimization-based approach. An underlying goal of the Sensor Mix Model is to assist in defining and understanding the complexity, uncertainty, and networked potential of aerial and ground platforms coupled with individual sensor capability. The requirement to understand the above components identifies a need to develop an overall model and methodology for suggesting an appropriate mix and allocation strategy for UA sensors in a given scenario.

The model takes as input an inventory of sensors and platforms, a list of configurations of assets known as packages, and an intelligence-based clustering of targets, and creates operationally feasible assignments of packages to target clusters that maximize the weighted number of targets detected. The model prioritizes detections by target type, and can be modified to prioritize them based on target location, as well.

This thesis uses techniques from stochastic optimization and mixed integer linear programming to accomplish this goal. Stochastic linear programs are able to account for uncertainty in the input data. Using this approach, the allocation or assignment of sensors suggested by the model is robust to uncertainties in sensor performance and available threat information (i.e. location, type and quantity of targets). Other factors taken into consideration include sensor characteristics such as cost, latency, logistical footprint, and survivability.

B. ASSUMPTIONS

There are several basic assumptions that allow for the development of the optimization models. The first assumption is that sensor performance data of the form used to develop the Sensor Mix Model is or will be available as input data. A second basic assumption is that a certain level of intelligence is available to the UA from other than organic assets (i.e. higher echelons, joint, national, etc). This initial level of

intelligence available to the UA is considered static during the period of time for which the model provides operational decision support.

For simplicity, an assumption is made that all sensor platforms are launched from a single location and are centrally controlled. However this assumption is easily modified to account for multiple launch locations.

Within the UA's Area of Interest, potential search areas are identified. Targets within these areas are assumed independent and randomly and uniformly distributed. Target speed is considered negligible in relation to searcher speed in the case of moving platforms.

A final basic assumption deals with consolidated packages and assumes a positive or enhanced capability when platforms are teamed to form consolidated packages. The above assumptions are further explained in this chapter and assist in maintaining the simplicity required to develop performance measures for input into the model.

C. PACKAGE CONSOLIDATION

In order to support the sensor allocation decisions, the Sensor Mix Model identifies the following levels of sensor aggregation: sensors, platforms, and packages. Sensors are identified as specific technologies or capabilities, such as infrared (IR), acoustic, and radar, and their performance can be measured by a probability of detection at a given range against a specific target type. Platforms have the capability to carry one or more sensors based on size, weight, and payload capacity. UA platforms are further identified as ground or aerial and moving or stationary and consist of such entities as the Unmanned Aerial Vehicle (UAV), Armed Robotic Vehicle (ARV), and Unattended Ground Sensor (UGS).

Finally, packages are defined as combinations of platforms based on the ability of the individual platform to enhance the collective sensing capability or performance of the package. A package consisting of two or more platforms is assumed to perform at least as well as two or more independent platforms. This (potentially) increased performance is the result of a platform's ability to cue another platform assigned to a package

configuration and provide a complementary target signature (i.e. sensors working together in a dependent relationship). Figure 5 summarizes the sensor aggregation levels through an example using four sensor types, three platforms, and two packages.

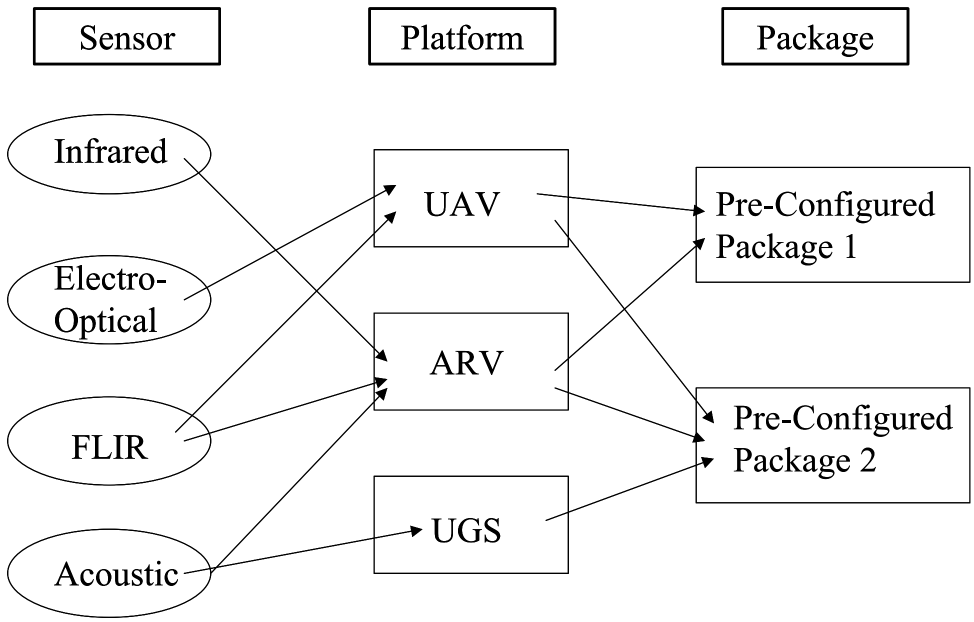

Figure 5. Sensor Aggregation Levels

The Unit of Action has a designated inventory of platforms organic to the unit. Each platform has one or more mounted sensors, and an average performance level based on underlying platform performance (i.e. velocity, operational time) and sensor performance (i.e. probability of detection against a specific target at a specific range). Platforms are combined to form pre-configured packages prior to assignment or allocation.

Packages consist of a single platform or multiple platforms. Single-platform packages and pre-configured packages containing multiple platforms are referred to as basic packages. Consolidated packages are combinations of basic packages, and are generated automatically.

In a single platform package, the performance of the package is the same as the performance of the platform. When multiple platforms are teamed together and designated as a pre-configured package, a combined platform performance is calculated

to determine an overall package performance level. Table 1 illustrates the set of example basic package configurations used in this thesis. Our model explicitly forms consolidated packages based on combinations of the basic packages provided by the user.

Table 1. Basic Package Configurations

Platform / Package ID	UAV Class I	UAV Class II	UAV Class III	UAV Class IVa	ARV	UGS
P1	**1**					
P2		**1**				
P3			**1**			
P4				**1**		
P5					**1**	
P6						**1**
P7	**1**	**1**				
P8			**1**	**1**		
P9			**1**		**1**	
P10				**1**		**1**

All packages, basic or consolidated, are considered single entities for employment or allocation purposes. For each package, overall performance is pre-calculated for use by the model, as explained in Section E.4. The Sensor Mix Model uses the performance of each package to determine an effective assignment of packages to target clusters.

D. TARGET CLUSTERING

A basic assumption is that a certain level of information is available to the UA commander through the UE IPB and the CROP, representing a commander's initial intelligence estimate of the situation. Uncertainty still exists in relation to 'true' or actual locations, type, and estimated number of targets on the battlefield.

Using the intelligence estimate provided to the UA, targets can be clustered, or grouped, together utilizing several different techniques. Such techniques include simple Euclidean distance-based clustering, terrain-based clustering, grouping by target type, or, possibly, more sophisticated statistical analyses. For simplicity, a Euclidean-distance based grouping was used in this thesis, and the term "target cluster" does not indicate that

targets are tactically related. Figure 6 provides an example of target clustering on the battlefield.

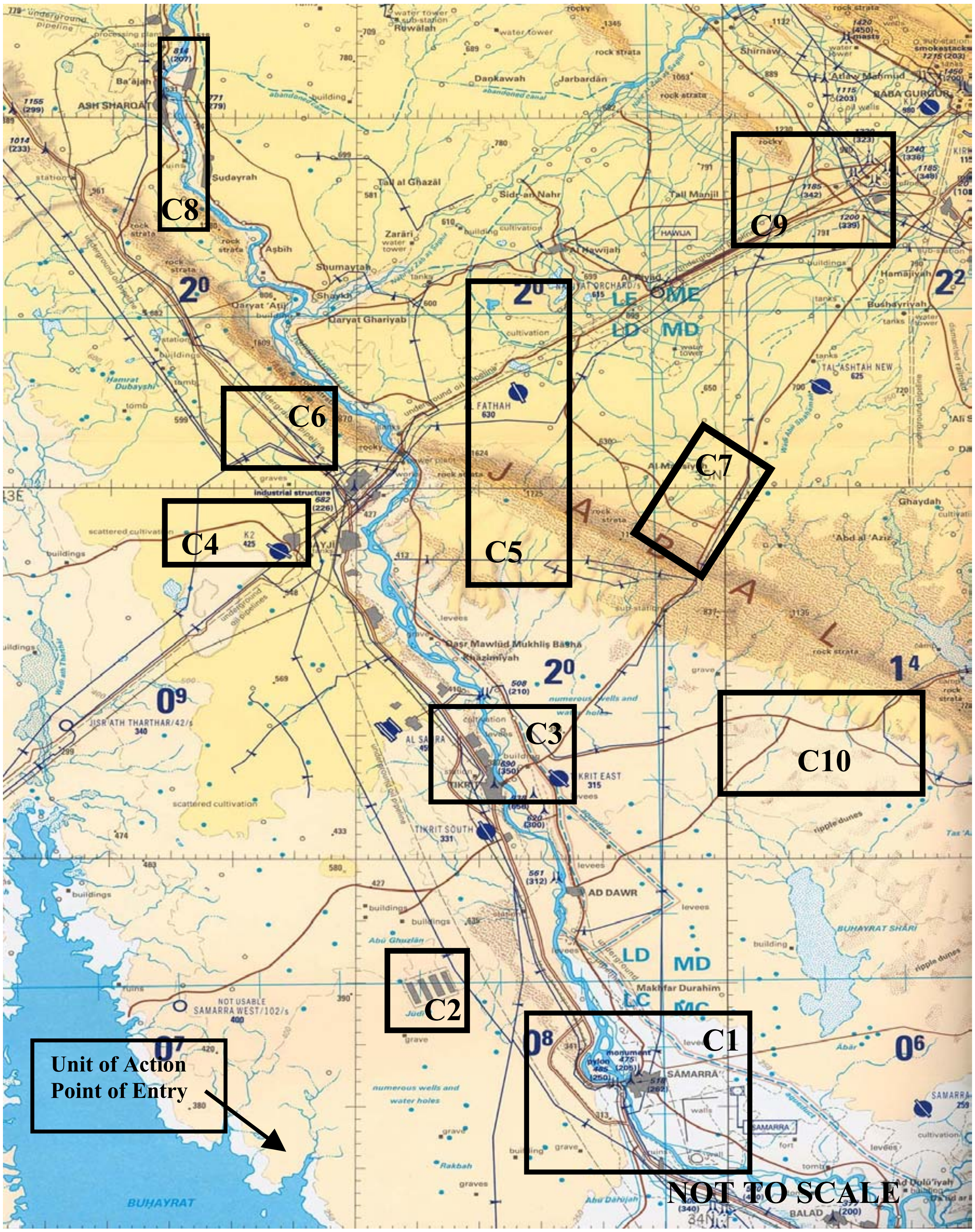

Figure 6.   Example of Target Clustering

The number of target clusters in the model was limited to ten for expository purposes. The number of clusters can vary based on user specification, outcome requirements, experimental design, etc. Target clusters also vary in size or dimension, as specified by the user as the model takes total cluster area into account in the calculations. Target clusters are then identified by dimension and approximate center grid location. Using the intelligence represented by Figure 6, Table 2 enumerates the target cluster dimension and location data, and represents a data input into our model that must be provided by the analyst, commander, or statistical clustering software.

Table 2. Target Cluster Dimension and Location Data

	Dimensions		Center Grid Coordinate	
Cluster Identifier	Length (km)	Width (km)	X	Y
C1	20	16	4360	3455
C2	20	15	4390	3430
C3	20	10	4375	3457
C4	10	5	4350	3485
C5	5	20	4392	3525
C6	15	10	4353	3505
C7	10	10	4397	3488
C8	5	15	4335	3540
C9	20	10	3520	3530
C10	17	14	3556	3574

E. METRIC DEVELOPMENT

A set of metrics is needed to represent individual sensor and platform capabilities and performance levels. Metrics are designed to assist decision makers in comparison studies and selection of the best course of action. For ease in calculation and

understanding, we partitioned metric development into the same three levels that define the UA aggregate sensor levels: sensor, platform, and package. This framework allows the user to provide inputs and receive outputs at each level and assists in determining the overall effectiveness of the desired system or platform allocation strategy.

Aerial and ground platforms have the ability to carry or maintain more than one type of sensor. Current information on UA sensor capabilities and platform configurations is under continual update. Table 3 below summarizes the current sensor/platform pairings as identified in the Future Combat Systems Book, Version 1.6. Entries in bold face are the basis for combinations used in this thesis and the Sensor Mix Model.

Table 3. Possible Sensor/Platform Configurations

Platform / Sensor	UAV Class I	UAV Class II 1,2	UAV Class III	UAV Class IVa 1,2,3	ARV-RSTA	UGS
Infrared	**640x480**	**640x480**		**yes**		yes
Electro-Optical	**small**	**small**	**medium**	yes	**Mast**	yes
Acoustic		yes	**yes**		**Yes**	**yes**
LWIR			yes	**yes**		
FLIR					**yes**	
LADAR			yes			
Seismic						**yes**
Magnetic						

Additional Capabilities: 1. Ground Moving Target Indicator
2. Synthetic Aperture Radar
3. See Through Foliage

1. Random Search Theory

The actions and capabilities of the different sensor aggregation levels (sensor, platform, package) are described and modeled by techniques from random search theory. The use of these techniques requires the following assumptions: (1) uniform and random target distribution throughout the search area, (2) the platform track is random but uniformly distributed, and (3) no search effort falls outside the search area (Stone, 1975).

The first assumption is reasonable for the level of detail associated with this model. For example, an enemy armor company defensive posture would deliberately

emplace individual tanks in a tactical manner and would not disperse them uniformly over a hundred kilometer square area. However, it is not clear whether non-uniform grouping would increase or decrease the expected number of targets detected. Target clusters and EOBs are aggregate inputs, and this assumption is kept in perspective with the understanding that target location, type, and quantity are not known with certainty.

The second assumption is reasonable if targets are expected to move unpredictably, and the third assumption is reasonable when total search area is significantly larger than the sensor's effective detection range.

Other search methods were considered such as exhaustive search theory and the inverse cube law. "Exhaustive search theory, however, has a tendency to overestimate sensor capability in relation to target detection and should be thought of as an upper bound on the effectiveness of searching a region" (Washburn, 1996). The inverse cube law is an approximation that is more appropriate when there is much less performance data available.

The decision to use random search theory was based on mathematical simplicity, type and amount of data available, and its ability to provide a lower bound on the effectiveness of a systematic search of a particular area (Stone, 1975). Random search theory provides an effective lower bound for the Sensor Mix Model and is a form of the law of diminishing rate of returns (Stone, 1975). Utilizing random search theory attempts to prevent significant overestimation of the detection capability of UA sensing assets.

2. Sensor Level Metric

The performance of a sensor is summarized by a function called the lateral range curve (Wagner, 1999). Each sensor detects targets with a certain probability at a certain range resulting in a lateral range curve for each specific sensor/target pair. Figure 7 illustrates a typical lateral range curve.

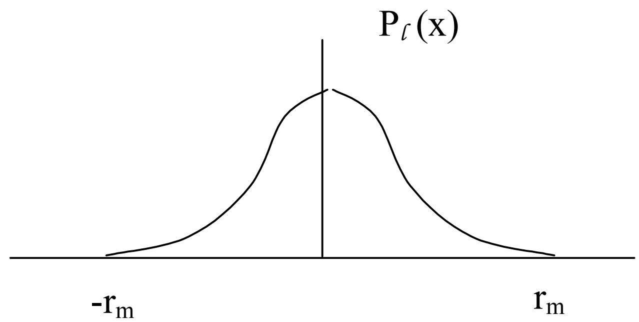

Figure 7. Lateral Range Curve (From Ref. Wagner, 1999)

Sensors are not guaranteed to move directly toward a target but will pass the target at some lateral range within the sensor's detection zone. Figure 8 below illustrates a sensor detection zone.

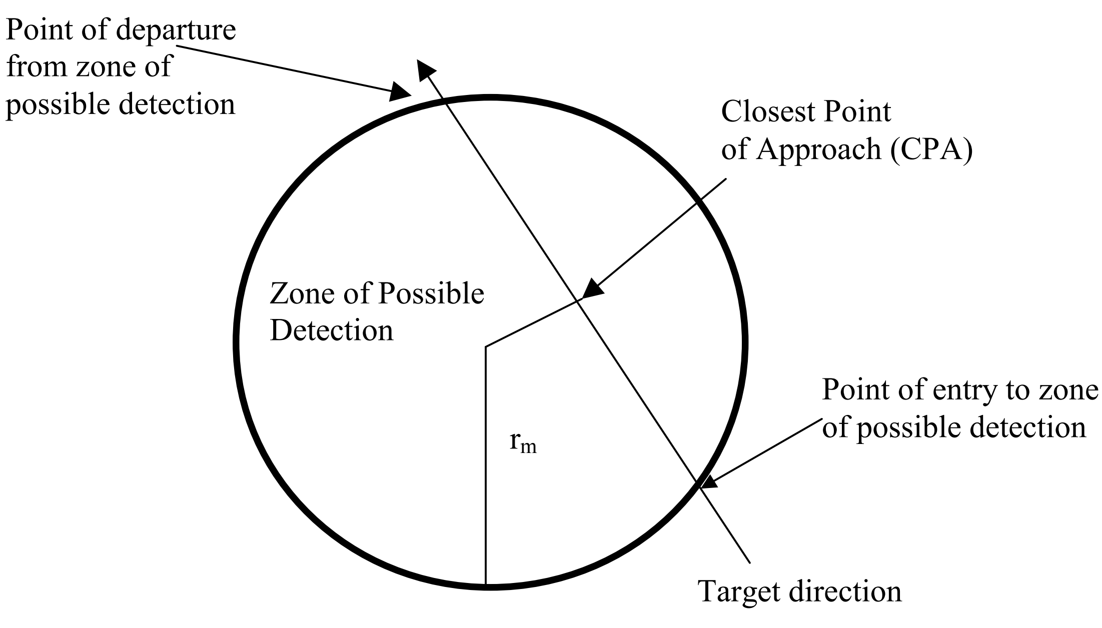

Figure 8. Sensor Zone of Detection (From Ref. Wagner, 1999)

Closely related to the lateral range curve is **sweep width (W)**, a scalar measure of the search effectiveness of a sensor (Washburn, 1996). By definition, sweep width is equal to the area under the lateral range curve and represents the effective width of the sensor detection zone:

$$W = \int_{-r_m}^{r_m} P_l(x)\,dx \tag{1}$$

Each sensor's performance can be represented as a probability of detection at a certain range against a specific target type. Using equation (1), a sweep width (W) is calculated for each sensor type against each possible target type. These will be used to generate cumulative detection probabilities for other levels of aggregation in Section 3 below.

A degree of uncertainty exists in relation to actual sensor performance. A sensor's performance level is affected by different factors such as terrain, weather, battlefield clutter, enemy deception tactics, etc. In order to account for the potential variation in sensor performance, four possible outcomes were modeled. Each outcome represented a different level of sensor performance based on several of the factors previously mentioned. Each outcome also had the possibility of each different EOB occurring. The ability to model this uncertainty assisted in providing a more robust allocation of assets to target clusters. Again, the number of outcomes developed is not limited to four but determined by the user.

3. Platform Level Metric

The platform metric is developed in terms of **Cumulative Detection Probability (CDP),** where CDP is the probability that a platform searching for a target over a specific time interval detects that target at least once (Wagner, 1999). Each platform CDP, or performance level, is determined by transit speed, sensing velocity, adjusted sweep width (defined in the next paragraph), and operational time.

a. Adjusted Sweep Width

When two or more sensors are mounted on a single platform, an adjusted sweep width must be calculated to account for the cumulative sensor capability on the platform. In order to determine the cumulative or total sensor capability for a single platform, the following assumptions are made: (1) the altitude at which the platform operates is optimal for all sensors, and (2) the sensor is considered a cookie-cutter sensor, meaning a target is detected the moment it enters the zone of detection and not detected beyond that range (Washburn, 1996).

The assumption that a platform operates at the optimal altitude for all mounted sensors is reasonable with the understanding that an appropriate combination of sensors has already been considered for a single platform. The second assumption that sensors are considered cookie-cutter does not realistically model sensor performance. Cookie-cutter sensors model the case where detection is certain within a certain radius and impossible outside of that radius. However, the cookie-cutter approximation is a convenient and reasonable device to allow fast, accurate calculation of time-dependent CDP values for various sensor-target pairings; a performance measure can be developed using lateral range curves with the additional understanding that each target has an independent closest point of approach that is large when compared to the sensor sweep width (Washburn, 1996).

Multiple sensors mounted on the same platform perform at least at the level of the best sensor and no better than the cumulative sum of all sensors. The sweep width calculated at the sensor level represents the performance of a sensor. By simply summing all the individual sweep widths, the sensing capability of a platform is significantly over-estimated and assumes complete independence between multiple sensors on the platform. This is an upper bound on the platform's sensor performance.

However, considering only the largest sweep width of all sensors on a platform tends to under-estimate the total capability of the platform and indicates a lower bound on the platform's sensor performance (sweep width). Using only the single largest sweep width assumes complete dependence between sensors, indicating no added benefit of more than one sensor on a single platform.

Therefore, an **adjusted sweep width** is calculated by selecting the maximum sweep width (lower bound on sensor performance for the platform) and applying a dependence factor to the remaining cumulative sum of the sweep widths. This result is

$$W_{adj} = \underset{s}{MAX}(w_s) + \alpha * \{\sum_s (w_s) - \underset{s}{MAX}(w_s)\} \quad (2)$$

where w_s represents individual sensor sweep widths, and α is a positive dependence factor indicating added benefit of multiple sensors mounted on a single platform.

The Sensor Mix Model methodology assumes a positive benefit from having multiple sensors working in concert. This benefit is due, in part, to the ability of sensors to cue other sensors to specific target locations on the battlefield, and multiple sensors detecting the same target providing a greater level of fidelity in that single detection.

b. Time on Station

Platform speed and operational time are directly related to platform size, fuel capacity, payload carrying capacity, etc. **Transit speed** is the speed at which the platform can travel to, and return from the search area. During transit to a search area, the platform is assumed to have its sensors in a passive mode, where no information is actively transmitted to the CROP. Platform **sensing velocity** is generally less than the platform transit speed and is the velocity at which a sensor is able to provide accurate detection capability at the level of resolution or fidelity required for the CROP. **Operational time** is the amount of time a platform can remain operational, including transit time and search time.

Using the Euclidean distance formula to calculate the distance from the platform launch site to the search area, and taking into account the platform transit speed, and total operational time, an associated **time on station** (time available over the search area) is determined by:

$$\text{Time On Station} = T_{op} - (2 * \frac{D}{V_t}) \qquad (3)$$

where T_{op} is total operational time, D is the distance to the search area, and V_t is transit speed.

c. Coverage Factor

Another important factor in the platform metric calculation is total search area covered. Fixing the total area of a target cluster, platform sensing velocity, time on station, and the adjusted sweep width, a **coverage factor** is determined. This factor is the ratio of cluster area swept by the given platform (Wagner, 1999).

The coverage factor for a particular platform is calculated as follows,

$$Coverage\ Factor = \frac{v_s W_{adj} t}{A} \qquad (4)$$

where v_s is the platform sensing velocity, W_{adj} is the adjusted sweep width of the platform, t is the time on station, and A is total area of the cluster.

d. Platform CDP

It has been shown (Wagner, 1999) that the probability of detection of a target by a platform can be expressed as

$$F_d(t) = 1 - e^{-\frac{vW_{adj}t}{A}} \qquad (5)$$

Given, that sensing velocity, adjusted sweep width, and time on station are fixed for a particular platform, expression (5) yields a constant probability of detection. We can model the coverage of a cluster by multiple platforms of the same type by

assuming that each individual platform "covers" an equal proportion of the cluster. It follows, then, that

$$F_d(p) = 1 - e^{-\frac{vW_{adj}t}{A\frac{1}{p}}} \qquad (6)$$

yields the probability of detection for p platforms searching within the target cluster. This expression is known as the Cumulative Probability of Detection (CDP). Figure 12 shows a graphical example of a CDP.

4. Package Level Metric

Basic packages are single platforms or combinations of platforms teamed together for various reasons. Teaming platforms has the potential to reduce the number of intervals where targets may be blocked from view and/or multiple signatures of the same target in the search area increase the probability and fidelity of a target detection (Klein, 1993). Consolidated packages are combinations of basic packages. Each package then has an associated overall CDP that is a combination of the individual platform CDPs.

Similar to multiple sensors on a single platform, a package has an overall CDP at least as good as the best individual platform. However, teamed platforms configured into basic and consolidated packages are assumed to have an improved performance level over independently employed platforms.

Summing the individual platform CDPs suggests complete independence and no overlap of search effort, which does not realistically represent multiple platforms over a search area. The high potential in overlap of search effort between platforms implies some type of dependence. However, substituting only the best individual platform performance as the overall package CDP implies the opposite, or a complete dependence between platforms and no added benefit is gained from teaming platforms.

A positive benefit is assumed with package configurations to account for cueing between platforms, enhanced performance, thoroughness of search area coverage, and the improved fidelity of information being processed and transmitted to the CROP.

A CDP is calculated for each individual platform (for each target type) using the platform's sensing velocity, adjusted sweep width, time on station, and area of the target cluster. Figure 9 shows an example of individual performance levels (CDP) for two platforms, if each independently searched target cluster 1.

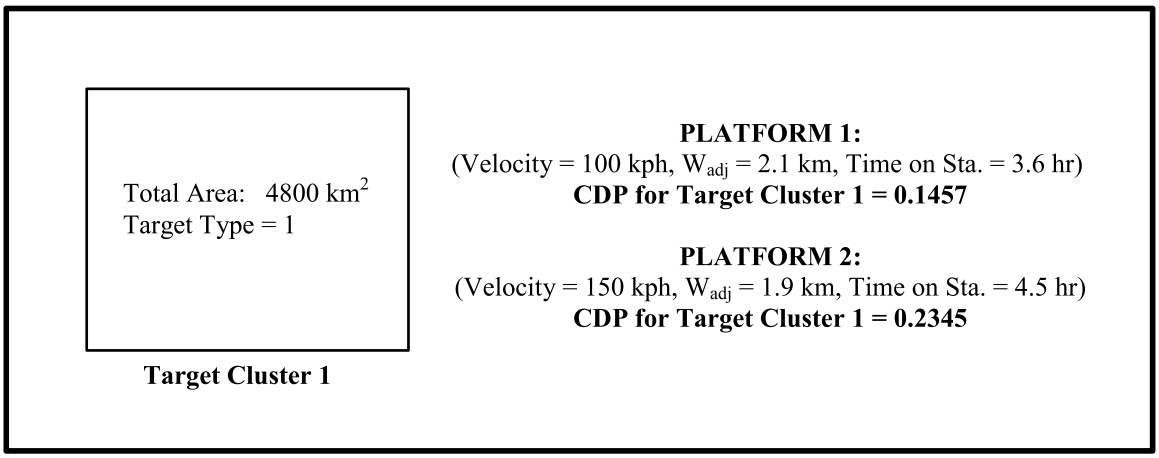

Figure 9. Individual Platform CDPs Associated with Target Type 1 in Target Cluster 1

The goal at the package level is to maximize the minimum CDP of all platforms in the same package and this occurs when all platforms have the same CDP. The proportion of the search area that each platform covers represents an effective distribution of the cluster area for the operating platforms.

Using platform 1 and platform 2 from Figure 9, and designating a package configuration, each platform searches a portion of the total area of the target cluster. Figure 10 shows a possible scenario where each platform is modeled as being responsible for fifty percent of the total area.

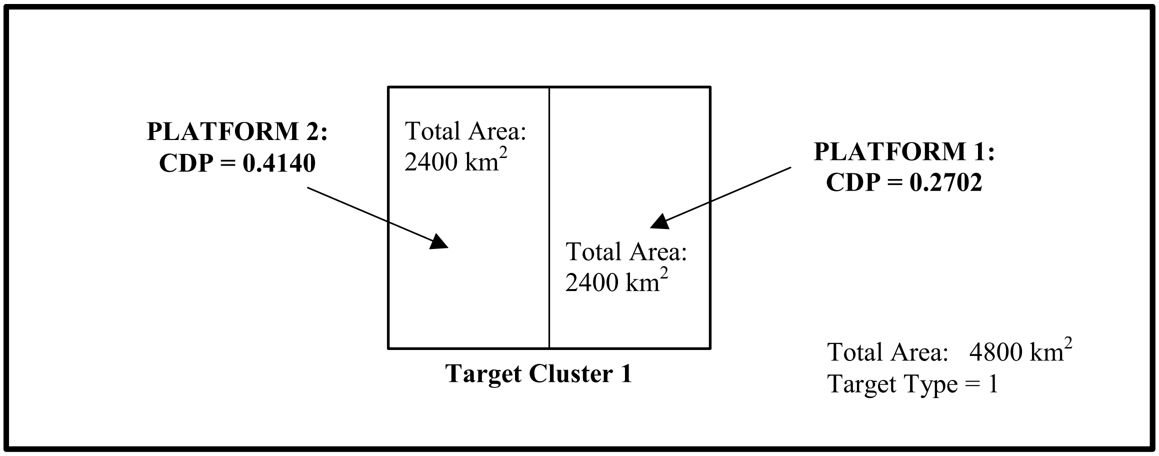

Figure 10. Visualization of Two Platforms Searching a Target Cluster (50% of the Area)

Since we have assumed uniform target distribution, the overall "effectiveness" of this package, then, is the simple average of the two CDPs (0.3421), which represents the expected proportion of all targets detected within the cluster. This is not the most efficient distribution of detection effort of the two platforms, however; the most efficient distribution of detection effort occurs when the minimum CDP is maximized (i.e., the two are equal).

To maximize the minimum CDP, each platform's search rate is calculated using sensing velocity, adjusted sweep width, and time on station. Equation 7 shows the calculation for a platform search rate:

$$Rate = vW_{adj}t \tag{7}$$

Using the search rate for a single platform (from Equation 7) and the proportion of the target cluster that the platform effectively covers (from Equation 8),

$$\text{EffProp} = \frac{Rate \text{ (single platform)}}{\sum Rate \text{ (all platforms in the pkg)}} \tag{8}$$

the package CDP is determined.

By determining the proportion of the target cluster effectively covered, we are in effect moving the solid center line in Figure 11 (equivalent to the solid line in Figure 10) to the right or left until all platforms in the package searching the target cluster have the same CDP.

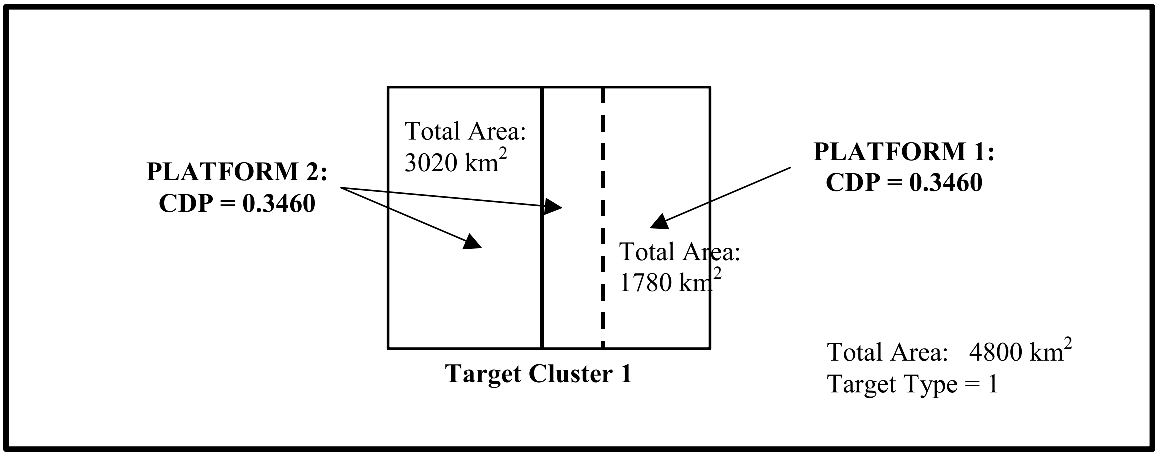

Figure 11. Visualization of Two Platforms Searching a Target Cluster (Effective Proportion of the Area)

Note that the overall effectiveness of the package as modeled in Figure 11 exceeds that shown in Figure 10 (0.3460 vs. 0.3421).

The package CDP is determined using the velocity, sweep width, and time on station of *any* platform in the package because each platform has the same CDP once the effective proportion of search area is determined (See Figure 11). The package CDP is calculated using a platform search rate (from equation 6) as follows,

$$CDP_{pkg} = 1 - e^{\left(-\frac{Rate}{A' * \beta_{pkg}}\right)} \tag{9}$$

where A' is the total area of the target cluster multiplied by the proportion of the total area effectively covered by the platform (See equation 7) and β_{pkg} is a positive dependence factor associated with a specific configuration of individual platforms designated as a package.

Figure 12 illustrates a CDP curve generated for multiple packages of the same type. As additional packages (of the same type) are allocated to a search area or target cluster the CDP increases asymptotically toward one (probability of detection $\leq$ 1).

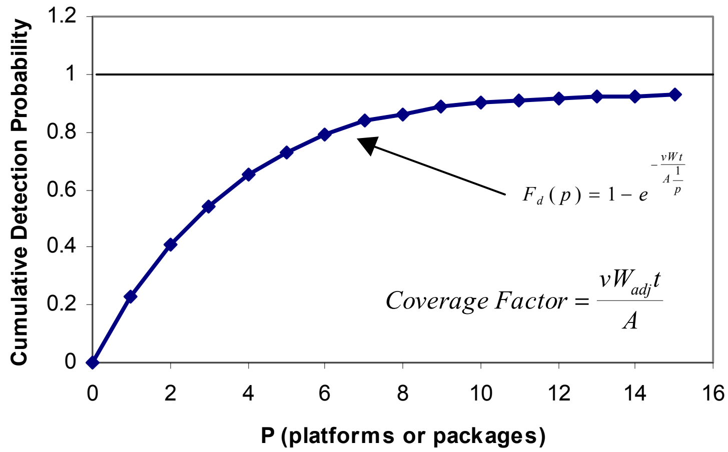

Figure 12. Cumulative Detection Probability Curve

F. ENEMY ORDER OF BATTLE

Although we assume prior intelligence regarding the Area of Operations, the previously mentioned uncertainty relating to location, type and quantity of targets on the battlefield is represented in the model as a list of potential Enemy Orders of Battle (EOBs). Again, using information from Figure 6 (number of target clusters designated by the user or commander), several EOBs are generated using intelligence available from higher echelons and entered as input to the model. Table 4 shows one possible EOB.

Four potential enemy EOBs were generated for this thesis to model the uncertainty associated with target location, type and number of entities for each identified target cluster. As with the number of target clusters, the user can specify any number of enemy EOBs to generate based on the experimental design or analysis being considered. Each EOB has a probability of occurrence that the model considers when determining a robust allocation of sensors to target areas.

Table 4. Enemy Order of Battle (sample)

	Estimated Number of Targets By Cluster									
Target Categories	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Rifleman, RPG, SOF	100	12				75				
Tracked Main Battle Tank			5	7						19
Special Purpose Artillery			4			4				
Wheeled Light Transport				6			11		5	
Tracked Armor Vehicle	125									15
Heavy Wheeled Transport					5	2				
Towed Artillery	30								4	
Wheeled Armor Vehicle				6				5		
Engineer Vehicle		4	4				6		7	
Tracked Missile Launcher						10				

G. SYSTEM CHARACTERISTICS

The final piece of the SMM and methodology consists of four identified characteristics associated with each individual sensor, platform, and package. The four characteristics are cost, logistical footprint, perishability (opposite of survivability), and latency. Each characteristic is calculated at each level of aggregation, and used at the package level to assess overall characteristics of the suite of packages employed.

The cost characteristic incorporates actual system (i.e. sensor and platform) replacement cost in dollars; however research and development costs were not included. Other costs include launch footprint or space required to deploy a platform (i.e. airstrip, catapult launch vehicle) and required operators to control an entire system (i.e. platform set-up, launch, employment, sensor payload management).

Logistical requirements include transportation requirements from actual equipment (hardware) deployment into theater to platform transport throughout the

theater of operations. Other factors considered were repair/replacement parts and equipment, fuel requirements, maintenance downtime (scheduled and unscheduled) and overall logistical footprint including operators, support personnel, facilities, etc.

Perishability is associated with the likelihood that a sensor or platform will be damaged or destroyed through enemy action or equipment failure before mission accomplishment. This characteristic additionally looks at the ability of the platform or sensor to perform subsequent missions.

Finally, latency defines a sensor's response time. This is identified as the delay between launch and a sensor becoming operational and having the ability to transmit information to the CROP. Latency is a function of bandwidth, transmission power, receiver location, etc.

The SMM allows the analyst or decision maker to provide a relative weighting to each characteristic category according to importance in the scenario or outcome. The objective function of the SMM incorporates these characteristics by minimizing their effects while maximizing expected number of targets detected in the search area.

H. MIXED INTEGER PROGRAMMING MODEL

The Sensor Mix Model is further characterized as a mixed-integer program (MIP). In a MIP, both continuous and integer variables are required to describe, quantify and qualify the inputs and states of the model.

Accurately modeling the sensor/platform-to-target allocation requires the use of non-linear functions to determine the expected probability of target detection. Difficulties arise in attempting to model or incorporate these non-linear measures of effectiveness into a linear optimization model.

In order to overcome the non-linearities, the solution was to enumerate a reasonable number of consolidated packages based on identified basic package configurations (see Table 1). Performance measures for these consolidated packages were pre-computed and provided as inputs for the model. For simplicity of example, this model enumerated only consolidated packages with up to two copies of up to two basic

packages, resulting in 175 available consolidated packages for consideration in the model. At this point the MIP solves the optimization problem using integer decision variables that represent the assignment of packages to target clusters. Chapter IV describes the model in detail and the resulting MIP formulation.

I. CURRENT DATA

Data currently available via Army Materiel Systems Analysis Activity (AMSAA) sources provides a lateral range curve and probability of detection for a particular sensor against a specific target type at a specified range. Table 5 provides a notional example of AMSAA data.

Table 5. Example of Sensor Data for Notional Sensor A Detecting Notional Target Type 1

Sensor Type: Sensor A	Target Type: Target 1
RANGE	**Probability of Detection**
100	0.954
200	0.943
300	0.907
400	0.876
500	0.854
600	0.791
700	0.723
800	0.643
900	0.532
1000	0.432
1100	0.310
1200	0.291
1300	0.121

Data similar to Table 5 provides the performance measure for individual sensors. However, performance measures for platforms carrying multiple sensors and consolidated packages (combinations of platforms) are currently unavailable. Using notional sensor performance data and platform performance (sensing velocity, time on station, etc), package performance levels were determined using random search theory, as described in Section E.1.

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IV. MODEL DESCRIPTION

The discussion of the Sensor Mix Model is divided into two main parts, the Sensor Allocation Model (how 'best' to allocate or assign a given set of sensors to target clusters), followed by the Sensor Mix Model itself (what is the 'best' mix of sensors for a given tactical scenario). Both models use many of the same parameters, inputs, and variables and are defined and described in the following sections. An additional set of constraints is defined for use in the Sensor Mix Model and a second integer decision variable is introduced.

A. SENSOR ALLOCATION MODEL

This section describes an optimization model that, given a fixed inventory of sensor platforms available, suggests an appropriate assignment of sensor packages to target clusters on the battlefield. The key decisions in the Sensor Allocation Model are which consolidated packages, and how many of each, should be assigned to each target cluster.

The mixed-integer program makes the best overall allocation of packages based on the mix available, taking into account the characteristic weightings of each package, target type weights, and sensor/platform performance. The decision variables for the Sensor Allocation Model are integer and indicate how many sensor packages of a certain type to allocate to a target cluster.

1. Indices

The indices used to define this model are:

p	platform type	{'UAV', 'ARV', 'UGS',...}
k	package configuration	{'K1', 'K2', 'K3',...}
t	target type	{'INF', 'Main Battle Tank', ...}

c target cluster {'C1', 'C2', 'C3',...}

ch sensor characteristic {'latency', 'cost', 'logistics', ...}

w outcome_scenario {'W1', 'W2', 'W3', ...}

eob enemy order of battle {'EOB1', 'EOB2', 'EOB3', ...}

n number of packages of type k to cluster c
{'N1','N2', ..., 'N10'}

Individual targets of type t are identified as being in one of ten target categories for the example in this thesis. The number of target categories can vary based on the user and desired results.

2. Parameters

The parameters used to define the data for this model are:

a. Asset Data

$plat\_pkg_{p,k}$ number of platforms of type p required for one package of type k

p_avail_p number of platforms of type p available (inventory)

$pkg\_char_{k,ch}$ value of package k contribution to each characteristic ch

$cdp_{c,t,k,w}$ Cumulative Detection Probability for package k against target type t in cluster c in outcome w

Table 6 shows the inventory level of organic UA platforms available for mission requirements. A brief description of each platform is provided in Appendix B.

Table 6. Unit of Action Sensor Platform Inventory (From Ref. ORD, 2002).

	Platform Type					
	UAV Class I	UAV Class II	UAV Class III	UAV Class IVa	ARV-RSTA	UGS
Inventory Level	54	36	12	27	27	99

b. Target Data

$num\_tgt_{t,c,eob}$ number of targets of type t in cluster c for a specific eob

c. Parameter Weights

wt_tgt_t value of detecting target type t

wt_char_{ch} platform characteristic weights

pr_eob_{eob} probability of a specific eob occurring

pr_out_w probability of a specific w occurring

$alpha\_det$ overall weight for expected targets detected portion of the objective function

$alpha\_char$ overall weight for characteristic portion of the objective function

The parameter weights listed above are described in Appendix B, Model Inputs.

d. *Derived Data*

$cdpe_{c,t,k,w,n}$ Cumulative Detection Probability Enumerated for n packages of type k against target type t in cluster c in outcome w

The model inputs are CDPs (indexed by target cluster, target type, package, and outcome) for one package, and the MIP precomputes the CDPs for assignment of up to ten packages of a single type assigned to a target cluster against a specific target type and indexes them by n. (See Chapter III.E.3 for a description of CDP).

3. Decision Variables

Unrestricted continuous variables in the model:

$CH\_OBJ_{ch,w}$ value of characteristic weights over all packages assigned to all clusters for an outcome w

$EXP\_TGT_{t,c,w}$ expected number of targets detected by target type t in cluster c for outcome w

OBJ objective function value

Integer variables in the model:

$KTOC_{c,k,w}$ Integer Variable: number of packages of type k assigned to cluster c in outcome w

Binary variables in the model:

$$IND\_VAR_{c,k,n,w} = \begin{cases} 1 & \text{if } n \text{ packages of type } k \text{ are} \\ & \quad \text{are assigned to cluster } c \text{ in outcome } w \\ 0 & \text{otherwise} \end{cases}$$

The key decision variables in the Sensor Allocation Model are integer and allow for the selection of which consolidated package, and how many are assigned to each target cluster.

4. Constraints

The model requires two main constraints. The first constraint set ensures that only one package type (regardless of configuration) is assigned to a target cluster.

$$\sum_{k,n} IND\_VAR_{c,k,n,w} \leq 1; \qquad \forall w, c$$

$$KTOC_{c,k,w} = \sum_{n} ord(n) * IND\_VAR_{c,k,n,w} \qquad \forall c, k, w$$

The second constraint ensures that only available platforms are used:

$$\sum_{c,k} plat\_pkg_{p,k} * KTOC_{c,k,w} \leq p\_avail_{p}; \qquad \forall p, w$$

The next two constraints calculate terms in the objective function.

$$\mathrm{EXP\_TGT}_{\mathrm{t,c,w}} = \sum_{eob,k,n} num\_tgt_{c,t,eob} * wt\_tgt_{t} * pr\_eob_{eob} * cdpe_{c,t,w,k,n} * IND\_VAR_{c,k,w,n}$$

$$CH\_OBJ_{ch,w} = \sum_{c} \sum_{k} KTOC_{c,k,w} * pkg\_char_{k,ch} * wt\_char_{ch,w}$$

The final constraint defines the objective as a weighted combination of expected, weighted targets detected and weighted sensor characteristics.

$$OBJ = alpha\_det * EXP\_TGT_{t,c,w} - alpha\_char * OBJ\_CH_{ch,w}$$

5. Objective Function

The objective in this model is to maximize the weighted combination of expected number of weighted detections and overall sensor characteristic penalties.

Maximize OBJ

6. Results

We implemented the model using GAMS with CPLEX as the solver. The results for the model using 10 basic packages uniquely configured into 175 consolidated packages and allocated to 10 target clusters over 4 enemy order of battles, are given in Table 7.

Table 7. Model Results

	CPLEX (version 7.5)
Presolver	417 rows and 23,481 columns eliminated
Problem Size	5528 rows, 52400 columns, 115080 nonzeros
OPTCR = 0.05	< 10 seconds
OPTCR = 0.0	< 10 seconds

(175 Packages versus 10 Target Clusters, 4 EOBs and 10 Target Categories)

CPLEX applies a 'presolve phase,' which reduces the size of the MIP. The parameter OPTCR is a relative measure of optimality, and provides a bound on how far from the best possible answer the solution is (OPTCR = 0.05 requires the solution to be within 5% of optimal). The smaller the OPTCR, the more time needed for the solver to find a solution.

Table 8 is an example of Sensor Allocation Model output. For example, the SAM allocated three copies of package 1 to target cluster 1 and two copies of package 1 to target cluster 3. Table 9 breaks down the assignment of consolidated package 118 to target cluster 4 into basic package components and total assets allocated.

Table 8. Sensor Allocation Model Sample Output

Clusters / Package ID	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
P1	3		2							
P17		5								3
P25					10				1	
P97						4				
P10							2	7		
P118				4						

Table 9. Assignment of P118 to Target Cluster 4

Basic Pkg / Assignment	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
P118			2					1		

Consolidated Package 118:

Basic Package Combinations: (See Table 1)
Package 3: UAV Class III x 1
Package 8: UAV Class III x 1
UAV Class IVa x 1
Total Assets Allocated to Cluster 4:
UAV Class III x 8
UAV Class IVa x 4

B. SENSOR MIX MODEL

The Sensor Mix Model is an extension of the Sensor Allocation Model. Both models use most of the same parameters and input data; however the Sensor Mix Model includes a second decision variable and requires an additional set of constraints further defined by the user and converts the initial platform inventories from parameters to decision variables. The new decision variables are integer for the Sensor Mix Model and represent the number of platforms of type p for the scenario modeled. The new constraints restrict the model from suggesting an unrealistic number of platforms for the UA sensor mix, based on various real limitations such as logistical footprint, cost, etc.

1. Indices

The indices used to define this model are:

p	platform type	{'UAV', 'ARV', 'UGS',...}
k	package configuration	{'K1', 'K2', 'K3',...}
t	target type	{'INF', 'Main Battle Tank', ...}
c	target cluster	{'C1', 'C2', 'C3',...}
ch	sensor characteristic	{'latency', 'cost', 'logistics', ...}
w	outcome_scenario	{'W1', 'W2', 'W3', ...}
eob	enemy order of battle	{'EOB1', 'EOB2', 'EOB3', ...}
n	number of packages of type k to cluster c	{'N1','N2', ..., 'N10'}

Individual targets of type t are identified as being in one of ten target categories for the example in this thesis. The number of target categories can vary based on the user and desired results.

2. Parameters

The parameters used to define the data for this model are:

a. Asset Data

$plat\_pkg_{p,k}$	number of platforms of type p required for one package of type k
$pkg\_char_{k,ch}$	value of package k contribution to each characteristic ch
$cdp_{c,t,k,w}$	Cumulative Detection Probability for package k against target type t in cluster c in outcome w

b. Target Data

$num\_tgt_{t,c,eob}$	number of targets of type t in cluster c for specific eob

c. Parameter Weights

wt_tgt_t	value of detecting target type t
wt_char_{ch}	platform characteristic weights
pr_eob_{eob}	probability of a specific eob occurring
pr_out_w	probability of a specific w occurring
$alpha\_det$	overall weight for expected targets detected portion of the objective function
$alpha\_char$	overall weight for characteristic portion of the objective function

The parameter weights listed above are described in Appendix B, Model Inputs.

d. *Derived Data*

$cdpe_{c,t,k,w,n}$ Cumulative Detection Probability Enumerated for n packages of type k against target type t in cluster c in outcome w

The model inputs are CDPs (indexed by target cluster, target type, package, and outcome) for one package, and the MIP precomputes the CDPs for assignment of up to ten packages of a single type assigned to a target cluster against a specific target type and indexes them by n. (See Chapter III.E.3 for a description of CDP).

3. Decision Variables

Unrestricted continuous variables in the model:

$CH\_OBJ_{ch,w}$ value of characteristic weights over all packages assigned to all clusters for an outcome w

$EXP\_TGT_{t,c,w}$ expected number of targets detected by target type t in cluster c for outcome w

OBJ objective function value

Integer variables in the model:

$KTOC_{c,k,w}$ Integer Variable: number of packages of type k assigned to cluster c in outcome w

P_AVAIL_p number of platforms of type p available (inventory)

Binary variables in the model:

$$IND\_VAR_{c,k,n,w} = \begin{cases} 1 & \text{if } n \text{ packages of type } k \text{ are} \\ & \quad \text{are assigned to cluster } c \text{ in outcome } w \\ 0 & \text{otherwise} \end{cases}$$

The primary decision variables for the Sensor Mix Model are integer and represent the number packages allocated to a particular target cluster and the number of platforms of each type to include in the UA inventory. The decision variable, P_AVAIL_p represented as a parameter in the Sensor Allocation Model is allowed to vary in the Sensor Mix Model. The SMM then determines a reasonable overall mix of sensor assets to include in the UA inventory by optimizing over several EOBs and possible outcomes.

4. Constraints

This model requires several of the same constraints used in the SAM. An additional set of constraints is added to define user restrictions that allow the model to solve and prevent the assignment of an unrealistic number of sensor assets for the UA inventory. Again, the first set of constraints ensures that only one package type is assigned to a target cluster.

$$\sum_{k,n} IND\_VAR_{c,k,n,w} \leq 1; \qquad \forall w, c$$

$$KTOC_{c,k,w} = \sum_{n} ord(n) * IND\_VAR_{c,k,n,w} \qquad \forall c, k, w$$

The second constraint set ensures only available platforms are used.

$$\sum_{c,k} plat\_pkg_{p,k} * KTOC_{c,k,w} \leq p\_avail_p; \qquad \forall p, w$$

The additional set of constraints required for the Sensor Mix Model are expressed in a general form below, indexed by i, and represent various constraints such as logistical considerations, personnel, budget, etc, on the choice of the integer decision variable P_AVAIL_p.

$$\sum_{p} a_{i,p} * P\_AVAIL_p \leq b_i; \qquad \forall i$$

An example of constraint set three,

$$\sum a_{\log,p} * P\_AVAIL_p \leq b_{\log}$$

where $a_{\log,p}$ represents the cargo space required for platform p on a C5 aircraft, and $b_{\log}$ represents total space available for transport of all platforms to theater. Without this set of constraints, the model would be unconstrained.

The next two sets of constraints calculate terms in the objective function.

$$\text{EXP\_TGT}_{\text{t,c,w}} = \sum_{eob,k,n} num\_tgt_{c,t,eob} * wt\_tgt_t * pr\_eob_{eob} * cdpe_{c,t,w,k,n} * IND\_VAR_{c,k,w,n}$$

$$CH\_OBJ_{ch,w} = \sum_c \sum_k KTOC_{c,k,w} * pkg\_char_{k,ch} * wt\_char_{ch,w}$$

The final constraint defines the objective as a weighted combination of expected, weighted targets detected and weighted sensor characteristics.

$$OBJ = alpha\_det * EXP\_TGT_{t,c,w} - alpha\_char * OBJ\_CH_{ch,w}$$

5. Objective Function

The objective in this model is to maximize the weighted combination of expected number of weighted detections and overall sensor characteristic penalties.

Maximize OBJ

V. CONCLUSIONS

This research has resulted in the development of models for optimally allocating sensor packages to target clusters on a battlefield and for determining an organic mix of sensors for the Unit of Action. A sensor package consists of a combination of platforms each carrying one or more sensors. The models ensure that platforms have sufficient range, time on station, and performance level for each enemy order of battle per target cluster so the maximum expected number of target detections occurs.

Two basic models were created. The Sensor Allocation Model, with a fixed mix- or inventory- of sensor platforms, allocates consolidated packages to target clusters. The second or Sensor Mix Model suggests a robust mix of sensor platforms over uncertainties in sensor performance and target quantity and location for consideration in development of the Objective Force structure or for task organization for a specific scenario. Both models take into account uncertainties in sensor performance and uncertainties in target location, type and quantity.

Both models pre-compute values for what would otherwise be non-linear model components (e.g. consolidated package performance for expected target detections). Integer variables represent the assignment of consolidated packages to target clusters resulting in a mixed integer linear program. An instance of the allocation model, with 10 basic packages, 10 target clusters, 4 enemy order of battles and 175 consolidated packages solved in less than ten seconds on a Pentium III processor.

A. RECOMMENDED MODEL REFINEMENTS

1. Data Improvements

Classified sensor data is available from AMSAA sources. The AMSAA data was reviewed to determine type and format available and a surrogate data set was generated to mirror the classified data and to develop our models. The assumption was made in development of the optimization models that platform and package performance data

would become available as further experimentation and research is conducted. The availability of such data would eliminate the need to surrogate the data in ways such as those described in Chapter 3, Section I (Metric Development) and in paragraph 2 (Dependence Factors) below. As additional sensor platform and package data becomes available, additional refinements and improvements to the models will be required.

2. Dependence Factors

The combination of sensors mounted on a single platform assumed a positive, or enhanced, overall platform performance. This positive dependence factor was applied to all sensor combinations. Further research may indicate that multiple sensors mounted on the same platform do not enhance performance in all situations and may possibly cause degradation in platform performance in some instances.

In similar fashion, combinations of platforms to form basic and pre-configured packages also assumed an enhanced performance level. Additionally, no particular criteria were used in determining basic pre-configured packages. The development of a methodology to optimize over individual platform performance to develop optimal package configurations should be considered for refining the models' package performance metric.

3. VV&A

Verification, Validation, and Accreditation have not been conducted on this model. TRAC-Monterey is in the process of developing the Dynamic Allocation of Fires and Sensor (DAFS) simulation. The output from the SAM and SMM can be used as input to the DAFS model. Validation would be accomplished by comparing the performance (in DAFS or other simulations) of sensor allocations suggested by the SMM to those derived by other means.

4. Target Clustering

The manner in which target clusters were identified for our models is perhaps too simplistic. Target clusters were based on proximity to nearby targets on the battlefield. A more effective method of clustering targets may include a statistical algorithm that groups targets by similarities or dissimilarities based on a series of inputs. A more refined method of identifying search areas and grouping targets could be incorporated to improve the model.

5. Sensor Characteristics

Four sensor characteristics (logistics, cost, perishability, latency) were identified through discussion and review of several Objective Force documents. The descriptions used for these terms are rather nebulous and difficult to quantify in meaningful measurements. As the Objective Force concept continues to develop, additional characteristics or methods to quantify the impact to operations can be identified and incorporated into the model.

B. SUGGESTED FURTHER RESEARCH

Many possibilities can be pursued to extend the models presented in this thesis. This thesis only addresses the allocation of organic Unit of Action sensor assets. However, our basic methodology easily adapts to echelons above or below the UA level. Minor modifications are needed to include joint assets at the higher echelons, and different mission requirements at both levels would have to be considered.

Another more challenging project would be to create a dynamic model significantly improving the utility of the presented models. There are two components for consideration in the development of a dynamic model. The inclusion of multiple time periods would take into account equipment or platform resupply, attrition rates, maintenance, follow-on missions, and new launch sites.

The second more difficult component would involve the allocation of a package to a higher priority or just-identified target area. This reallocation would also apply to

reallocation to a secondary target area if the allocation to the original target area was no longer required (i.e. mission change, combat damage assessments show target area clear, etc).

Further extensions of the models would allow for consolidated packages to search multiple target areas. This could be modeled based on a prioritization of target clusters and involve platform time on station. A more difficult scenario would allocate a consolidated package to search a primary target cluster, then “decompose” the consolidated package into basic package configurations. The resulting basic packages would then be reconsolidated into newly formed consolidated packages and optimized for allocation to secondary target clusters. New variables will be necessary to indicate package location, remaining time on station, and distance to secondary search area.

APPENDIX A: MODEL SET-UP

A. GENERAL ALGEBRAIC MODELING SYSTEM

The Sensor Mix Model uses the General Algebraic Modeling System (GAMS), a high level modeling system for mathematical problems. The GAMS program allows the user to represent large, complex models in a concise and compact fashion as well as supports expandability and the ability to provide clarifying documentation during programming. Additionally, GAMS was selected for the program's ability to automate data calculation and facilitate the import and export of data to and from other computer packages (McCarl, 2002).

B. DECISION SUPPORT INTERFACE

Microsoft Excel was used to pre-calculate values at each of the metric levels and provided an easy method in which to develop Include tables for use in GAMS. The Excel workbook was divided into three sections; user input, pre-processor, and data management. Additionally this software was selected for its ease in use and familiarity to most users.

1. User Input

The user input section contains a list of available platforms based on data available and current platforms in the Objective Force inventory. The user must select the number and type of platforms organic to the respective OF unit. Additional inputs include approximate location of the UA's entry into the theater of operations and/or platform launch site, approximate center grid location, and dimensions of identified target cluster areas in the battlespace.

Figure 13 shows an example of the current user interface that allows for organic platform information entries.

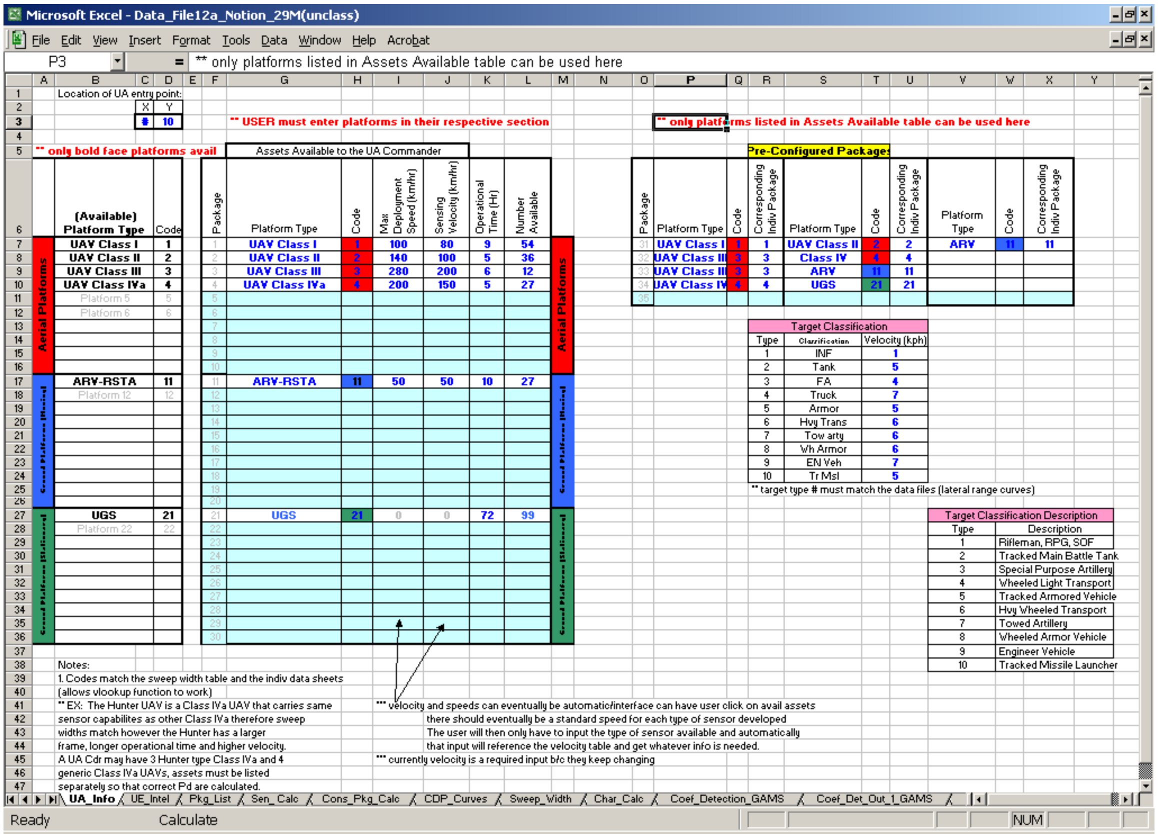

Figure 13. Excel Screen Shot of the User Interface

Required User Inputs:

- Unit Point of Entry or Platform Launch Site (grid coordinate)
- Selected Platforms in the Unit Inventory
- Maximum Deployment Speed and Sensing Velocity (km/hr)
- Pre-Configured Packages
- Estimated Target Velocities (km/hr)

Other required user inputs include target cluster dimensions and locations on the battlefield. Figure 14 is an example of the target cluster input worksheet.

	Cluster Dimensions		Cluster Locations	
Cluster	Length (km)	Width (km)	Center Grid Coordinate X	Center Grid Coordinate Y
1	20	16	4360	3455
2	20	15	4390	3430
3	20	20	4375	3457
4	10	5	4350	3485
5	5	20	4392	3525
6	15	10	4353	3505
7	10	10	4397	3488
8	5	15	4335	3540
9	20	10	3520	3530
10	20	30	3570	3565

Figure 14. Target Cluster Input Worksheet

Required User Inputs:

- Target Cluster Dimensions (km)
- Center Grid Coordinates

2. Data Management

The data management section is based on the information available through experimentation, real-world experience and expert input. For each available sensor type a sweep width is determined using the definitions of lateral range curve and sweep width. Figure 15 is an example of the data management section that calculates an adjusted sweep width in order to determine a platform performance level.

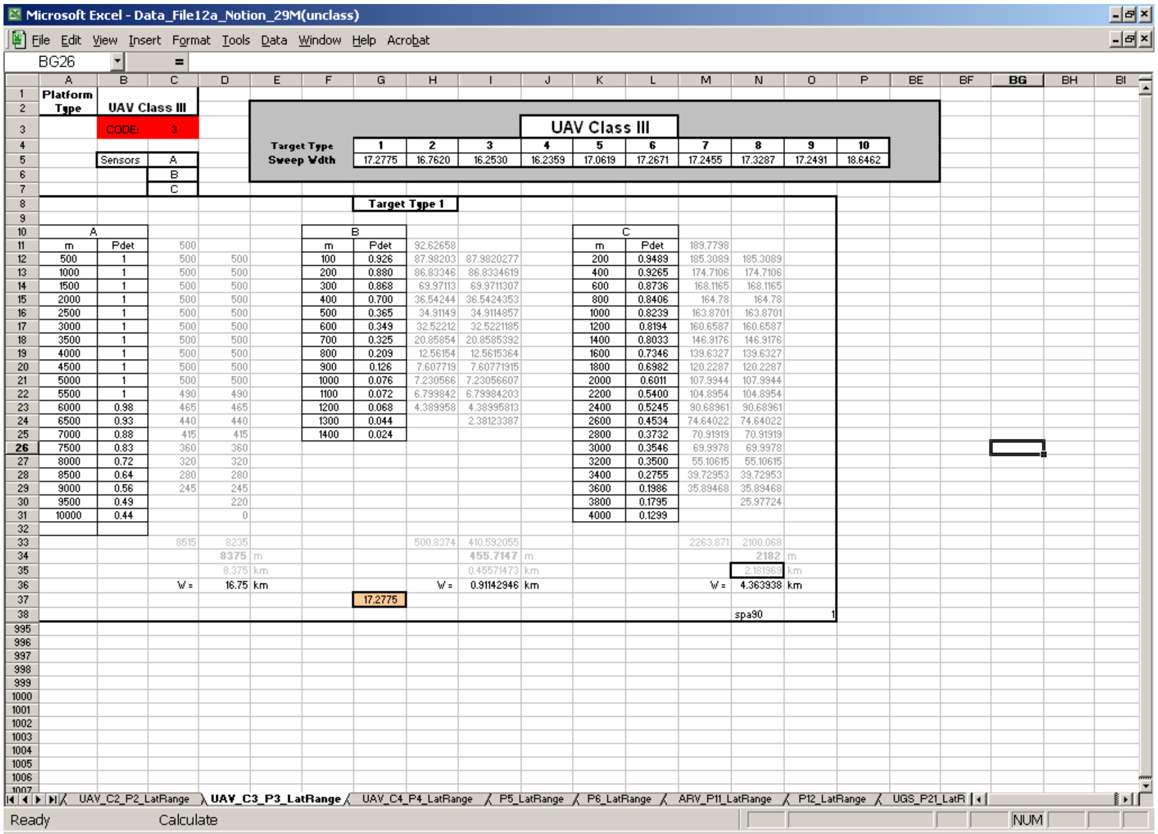

Figure 15. Example of Data Management Section

Each individual sensor mounted on a particular platform has an associated lateral range curve. The lateral range curves shown in Figure 15 indicate a range and a probability of detection at that range for each sensor (identified as sensor A, B, and C). The area under the lateral range curve is calculated and individual sensor sweep widths are determined. The individual sensor sweep widths and sensor dependence factors are used to determine an adjusted sweep width for use in the platform performance calculations.

The number of adjusted sweep widths required equals the number of target categories identified.

3. Pre-Processor Calculations

The pre-processor calculation section uses inputs from the user and data management sections to calculate required input for the GAMS model. Required pre-processor calculations include such things as platform time on station (hr), target cluster search area (km^2), platform characteristic information, and consolidated package performance measures. Additional inputs include a sensor dependence factor, an operating time period (time step) and platform characteristics. These inputs are not considered general user inputs but are designed as place holders for modifications and extensions of this model.

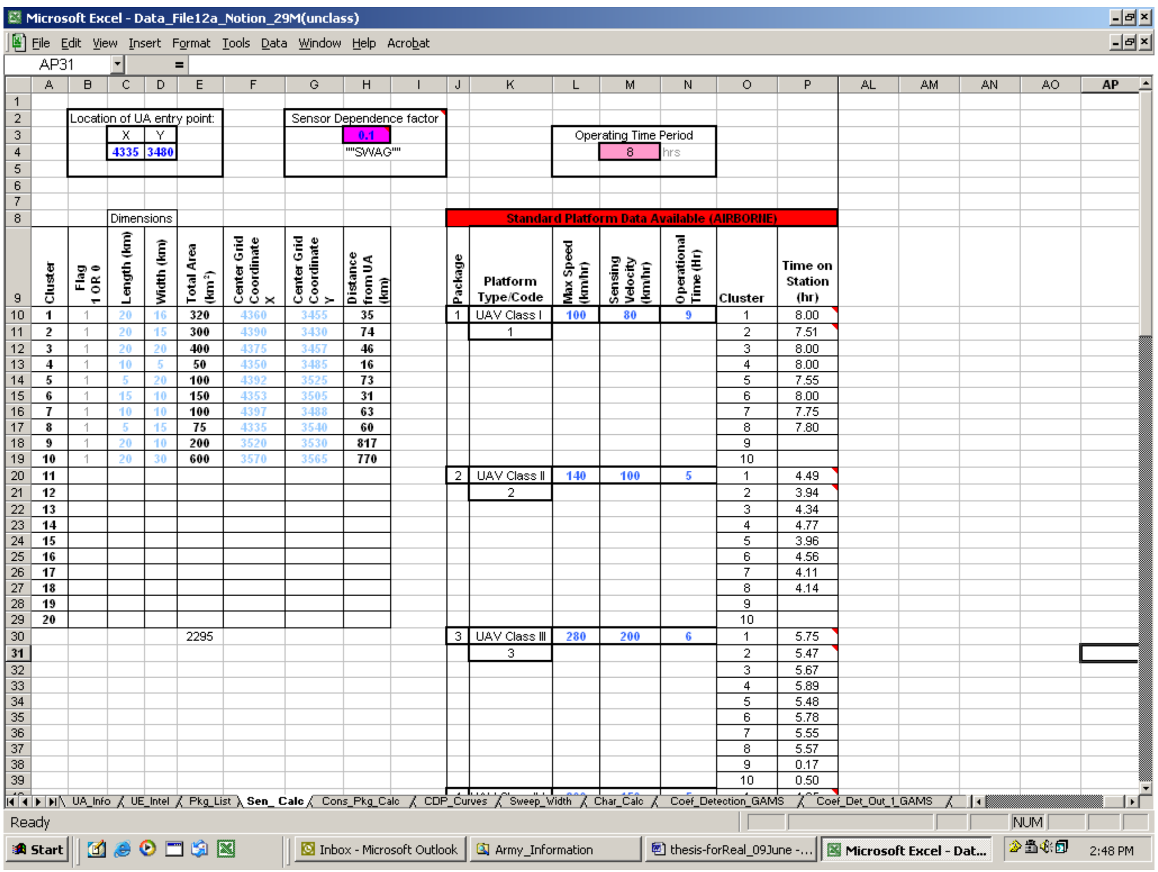

Figure 16. Platform Pre-Calculations (sample)

Platform Pre Calculations Required:

- Total Cluster Area (km^2)
- Distance from Platform Launch Site to Target Cluster (km)
- Time on Station (by platform per target cluster) (hr)

Code	Platform	Latency	Cost	Perishability	Logistics
1	UAV I	0.6	0.1	0.2	0.3
2	UAV II	0.5	0.3	0.2	0.4
3	UAV III	0.3	0.7	0.8	0.5
4	UAV IVa	0.1	1	1	0.7
11	ARV	0.4	0.8	0.4	0.1
21	UGS	1	0.2	0.15	0.05

** User inputs are BLUE

Figure 17. Platform Characteristics – User Input (sample)

Package	Latency	Cost	Perishability	Logistics
1	0.6	0.1	0.2	0.3
2	0.5	0.3	0.2	0.4
3	0.3	0.7	0.8	0.5
4	0.1	1	1	0.7
5				
6				

Figure 18. Platform Characteristics Pre-Calculations (sample)

Characteristic Pre-Calculations Required:

- Latency (maximum value of any platform in the package)
- Cost (total cost of all platforms in a package)
- Perishability (minimum value of any platform in the package)
- Logistics (minimum value of any platform in the package)

Cluster	1
Total Area	
2500	km^2

if there is a cluster -need to calculate each packages CDP for each target catego b/c any or all tgt could be in the cluster

	Package Type						Package Type				
	UAV Class I	UAV Class II	UAV Class III	UAV Class IVa	ARV-RSTA	UGS					
Target Type	1	2	3	4	11	21					
	1	2	3	4	11	21	31	32	33	34	35
1	0.34	0.404	0.46	0.4765	0.444	0.208	0.576	0.60	0.52	0.51	0.55
2	0.26	0.324	0.38	0.3965	0.364	0.128	0.496	0.52	0.44	0.43	0.47
3	0.43	0.494	0.55	0.5665	0.534	0.298	0.666	0.69	0.61	0.60	0.64
4	0.31	0.374	0.43	0.4465	0.414	0.178	0.546	0.57	0.49	0.48	0.52
5	0.298	0.362	0.418	0.4345	0.402	0.166	0.534	0.56	0.48	0.47	0.51
6	0.209	0.273	0.329	0.3455	0.313	0.077	0.445	0.47	0.39	0.38	0.42
7	0.324	0.388	0.444	0.4605	0.428	0.192	0.56	0.59	0.50	0.50	0.54
8	0.331	0.395	0.451	0.4675	0.435	0.199	0.567	0.59	0.51	0.50	0.55
9	0.398	0.462	0.518	0.5345	0.502	0.266	0.634	0.66	0.58	0.57	0.61
10	0.252	0.316	0.372	0.3885	0.356	0.12	0.488	0.52	0.43	0.42	0.47

Cluster	2
Total Area	
3000	km^2

	Package Type						Package Type				
	UAV Class I	UAV Class II	UAV Class III	UAV Class IVa	ARV-RSTA	UGS					
Target Type	1	2	3	4	11	21					
	1	2	3	4	11	21	31	32	33	34	35
1	0.36	0.424	0.48	0.4965	0.464	0.228	0.596	0.62	0.54	0.53	0.57
2	0.28	0.344	0.4	0.4165	0.384	0.148	0.516	0.54	0.46	0.45	0.49
3	0.45	0.514	0.57	0.5865	0.554	0.318	0.686	0.71	0.63	0.62	0.66
4	0.33	0.394	0.45	0.4665	0.434	0.198	0.566	0.59	0.51	0.50	0.54
5	0.318	0.382	0.438	0.4545	0.422	0.186	0.554	0.58	0.50	0.49	0.53
6	0.229	0.293	0.349	0.3655	0.333	0.097	0.465	0.49	0.41	0.40	0.44
7	0.344	0.408	0.464	0.4805	0.448	0.212	0.58	0.61	0.52	0.52	0.56
8	0.351	0.415	0.471	0.4875	0.455	0.219	0.587	0.61	0.53	0.52	0.57
9	0.418	0.482	0.538	0.5545	0.522	0.286	0.654	0.68	0.60	0.59	0.63
10	0.272	0.336	0.392	0.4085	0.376	0.14	0.508	0.54	0.45	0.44	0.49

Figure 19. Package Performance Pre-Calculation (sample)

Performance Pre-Calculation Required:

- Cumulative Detection Probability
    - Requirements:
        - Platform Sensing Velocity (user input section)
        - Adjusted Sweep Width (data management section)
        - Time on Station (pre-processor section)
        - Total Cluster Area (pre-processor section)
    - Random Search Theory (Equation 1)
- Pre-configured Package Calculations
    - Requirements:
        - Platform Sensing Velocity (user input section)
        - Adjusted Sweep Width (data management section)
        - Time on Station (pre-processor section)
        - Total Cluster Area (pre-processor section)
    - Coverage Factor (per platform in target cluster area)

4. Include Tables (GAMS)

Based on the above calculations, the following GAMS Include tables are constructed and saved as .CSV files.

- Table 1: Cumulative probability of detection table indexed by package type, target type, target cluster location, and outcome
- Table 2: Package characteristic weighting table indexed by package type and characteristic category
- Table 3: Target cluster composition table indexed by target type and target cluster location
- Table 4: Platform inventory table

APPENDIX B. MODEL INPUTS

A. UNIT OF ACTION ORGANIC PLATFORMS

Unmanned Aerial Vehicle – Class I

An FCS unmanned aerial vehicle that provides the UA with a reconnaissance and security/early warning capability.

Unmanned Aerial Vehicle – Class II

An FCS unmanned aerial vehicle that is a multifunctional aerial system capable of providing reconnaissance, security/early warning, target acquisition and designation.

Unmanned Aerial Vehicle – Class III

An FCS unmanned aerial vehicle that is a multifunctional aerial system capable of providing reconnaissance, security/early warning, target acquisition and designation for precision fires throughout an area of influence.

Unmanned Aerial Vehicle – Class IVa

An FCS unmanned aerial vehicle that is multifunctional aerial system capable of providing reconnaissance, security/early warning, long endurance persistence stare, and wide area surveillance and has the ability to team with air-ground forces throughout the UA.

Armed Robotic Vehicle –

An FCS unmanned system that remotely provides reconnaissance capability in MOUT and other battlespace as well as remotely deploy sensors.

Unattended Ground Sensors-

An FCS unmanned system that provides the capability to carry a set of common payloads.

B. PARAMETER WEIGHTS

The tables in the following sections provide the parameter weights used in the notional data set generated for the Sensor Allocation Model and the Sensor Mix Model. The weights should sum to one and are set by the user based on the analysis or experiment.

Table 10. Target Weights (sample)

Target Categories	Model Input Weight
Rifleman, RPG, SOF	.03
Tracked Main Battle Tank	.10
Special Purpose Artillery	.13
Wheeled Light Transport	.07
Tracked Armor Vehicle	.10
Heavy Wheeled Transport	.07
Towed Artillery	.13
Wheeled Armor Vehicle	.10
Engineer Vehicle	.07
Tracked Missile Launcher	.20

Table 10 is a listing of target weights for the different target categories identified for this thesis.

Table 11. Characteristic Weights (sample)

Characteristic Category	Weight
Latency	.2
Cost	.6
Logistical Footprint	.1
Logistics	.1

Table 11 is a listing of characteristic category weights. This allows the user to adjust the weights based on importance of characteristic or weight them equally.

Table 12. Enemy Order of Battle Weights (sample)

Enemy Order of Battle	Probability of Occurrence
EOB1	.25
EOB2	.25
EOB3	.25
EOB4	.25

Table 12 lists the probability of a specific enemy order of battle occurring.

Table 13. Outcome_Scenario Weights (sample)

Outcome_Scenario	Probability of Occurrence
W1 (good terrain – good weather)	.01
W2 (good terrain – bad weather)	.15
W3 (bad terrain – good weather)	.24
W4 (bad terrain – bad weather)	.6

Table 13 lists the probability of a specific outcome_scenario occurring.

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APPENDIX C. GAMS CODE

```
*** Sensor Allocation Model Program ***
***  Modification #12 (29 May 2003 - Tutton)

$TITLE SMSNPS: Sensor Mix Model at Naval Postgraduate School  03.05.29
$INLINECOM { }
 OPTIONS
   SOLPRINT =    OFF,
   DECIMALS =      2,
   LIMCOL   =      2,
   LIMROW   =      2,
   RESLIM   =   60000, {max seconds}
   ITERLIM  =99999999, {max pivots}
   OPTCR    =    0.00, {relative integrality tolerance}
   RMIP     =   cplex,
   MIP      =   cplex
 ;
$maxcol 1000

 SETS
 p platforms /P1*P30/,
 k packages /K1*K175/,
 t  targets /T1*T10/,
 w  outcome_scenario /W1*W4/,
 c clusters /C1*C10/,
 eob enemy_order_battle /EOB1*EOB4/,
 ch characteristics /Latency,Cost,Perishability,Logistics/
 n max_number_pkg /N1*N10/
;
```

```
 ALIAS
   (kp,k)
;
***Scenario-specific data values***
 table Table12_Tgt(t,eob,c)
$ONDELIM
$INCLUDE H:\THESIS\Attempt12\Table12_Tgt.csv
$OFFDELIM
;
 table Table12_char(k,ch)
$ONDELIM
$INCLUDE H:\THESIS\Attempt12\Table12_char.csv
$OFFDELIM
;
 table Table12_CDP(c,t,w,k)
$Ondelim
$INCLUDE H:\THESIS\Attempt12\Table12_CDP.csv
$offdelim
;
 table Table12_plat(p,k)
$ondelim
$INCLUDE H:\THESIS\Attempt12\Table12_plat.csv
$offdelim
;

 PARAMETERS
wt_tgt(t) /
T1 .03,T2 .10,T3 .13,T4 .07,T5 .10,T6 .07,T7 .13,T8 .10,T9 .07,T10 .20
/,
pr_out(w) /
W1 .01,W2 .15,W3 .24,W4 .6
/,
```

```
pr_eob(eob) /
EOB1 .25,EOB2 .25,EOB3 .25,EOB4 .25
/,
p_avail(p) /
P1 54,P2 36,P3 12,P4 27,P11 27,P21 99
/,
wt_char(ch)/
Latency 0.2,Cost 0.6,Perishability 0.1,Logistics 0.1
/,
alpha_det        obj function weight for fraction target detected /0.9/,
alpha_char       obj function weight for overall characteristics /0.1/
;
* GAMS calculates the convex curves for 1 to 10 packages of type k sent to
* cluster c against target type t; 4000 calculations
* (10 tgt type x 10 clusters x max 10 of one specific package x 40 poss pkgs)
 PARAMETER cdpe(c,t,w,k,n)     CDP indexed by 1 to max number of package type k
sent to each cluster;
      loop(c,
          loop(t,
              cdpe(c,t,w,k,n) = 1 - (1 - Table12_cdp_bogus(c,t,w,k))**ord(n) ) )
;
 INTEGER VARIABLES
   KTOC(c,k,w)        "Number of packages of type k sent to cluster c"
;
 BINARY VARIABLES
   IND_VAR(c,k,w,n)   "Indicator variable: number of packages type k sent to cluster c"
;
 VARIABLES
   OBJ
   CH_OBJ(ch,w)
   EXP_TGT(t,c,w)
;
```

```
 EQUATIONS
   PKG_ASSIGN(c,k,w)
   PACK_CONSTR(c,w)
   TOT_TGT_DET(t,c,w)
   PACKAGES(p,w)
   CH_OBJ_CALC(ch,w)
   OBJ_CALC
 ;
* Number of packages k assigned to cluster c assigned based on binary var
* IND_VAR indicating 1 to 10 packages to cluster c
* ord(n) - returns the position of this set element within the overall set
PKG_ASSIGN(c,k,w)..
    KTOC(c,k,w) =E= sum(n,ord(n)*IND_VAR(c,k,w,n) )
;
PACK_CONSTR(c,w)..
    sum( (n,k), IND_VAR(c,k,w,n) ) =L= 1
;
TOT_TGT_DET(t,c,w)..
    EXP_TGT(t,c,w) =E= sum( (eob,k,n), Table12_Tgt(t,eob,c) * pr_eob(eob) *
cdpe(c,t,w,k,n) * IND_VAR(c,k,w,n) )
;
*Constrains number of packages created by number of platforms
* of type p available (inventory)
 PACKAGES(p,w)..
   sum( (c,k), Table12_plat(p,k)*KTOC(c,k,w)) =L= p_avail(p)
  ;
* Calculates 'overall' objective for each characteristic across each package for
* the number of packages of type k formed and sent to a cluster
 CH_OBJ_CALC(ch,w)..
   CH_OBJ(ch,w) =E= sum((k,c), Table12_char(k,ch)* KTOC(c,k,w) )
  ;
```

```
* Overall Objective:
 OBJ_CALC..
   OBJ =E= sum(w, pr_out(w)* (alpha_det* sum((c,t),EXP_TGT(t,c,w)*wt_tgt(t) )
          - alpha_char*sum(ch,wt_char(ch) * CH_OBJ(ch,w)) ))
  ;
 MODEL SMS /All/;
SMS.workspace = 10;
SMS.OPTFILE = 1;

 SOLVE SMS USING MIP MAXIMIZING OBJ;
 PARAMETER TGT_FOUND(t,w), TGT_EXIST(t);
 TGT_FOUND(t,w) = sum(c,EXP_TGT.l(t,c,w) )
;
        TGT_EXIST(t) = sum((c,eob),pr_eob(eob)* Table12_Tgt(t,eob,c))
;
 DISPLAY KTOC.l, CH_OBJ.l, EXP_TGT.l, TGT_FOUND, TGT_EXIST;
```

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